Three Essays in Applied Health Economics

by

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This dissertation is dedicated to my family - Mom, Dad, Trev, and Stephanie - and to all the animals who rescue us, including Ester, Kolt, and Clara.

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TABLE OF CONTENTS

LIST OF FIGURES

Figure

LIST OF TABLES

Table

LIST OF APPENDICES

Appendix

ABSTRACT

In this dissertation study, I examine three issues in applied health economics within the context of the Medicare program. Medicare provides health insurance coverage to the elderly and the disabled. Although the core components of Medicare have remained largely intact since its introduction in 1965, the program has undergone a number of changes in recent decades. During this period, program enrollment and costs have increased dramatically, and Medicare continues to play an increasingly prominent role in the U.S. health care system. In this study, I examine several integral aspects of the Medicare program, and, in doing so, I contribute to our understanding of health economics more broadly.

In Chapters 1 and 2, I focus on the interaction between the incentives of private health insurers that operate in the Medicare program and externalities from prescription drugs. More specifically, I test the hypothesis that integrated plans that provide coverage for drug and non-drug expenditures within the Medicare program internalize negative externalities from prescription opioids; because of the breadth of coverage that these plans provide, they have an incentive to consider adverse health outcomes that are linked to opioid use. Using Medicare Part D drug utilization data, I find evidence that supports this hypothesis in Chapter 1; relative to enrollment in a stand-alone drug plan, enrollment in an integrated plan lowered the probability of high dosage opioid use linked to hospitalizations by 32 percent in 2008 and 2009.

In Chapter 2, I extend my research question towards benefit design for prescription opioids. Because benefit design directly impacts enrollee drug use, I hypothesize that

integrated plans that operate within the Medicare Part D program structure benefits in a way that limits enrollees' use of high dosage opioids. To examine this issue, I test for differences in benefit design for opioids across integrated plans and stand-alone drug plans. I find that, relative to opioids covered by stand-alone drug plans, opioids covered by integrated drug plans are more likely to have a quantity limit restriction. Furthermore, conditional on a quantity limit restriction, opioids covered by integrated plans have lower opioid dosage allowances relative to opioids covered by stand-alone plans. These results reinforce the finding that integrated plans internalize negative externalities from prescription opioids, and they provide evidence of a mechanism through which this occurs.

In Chapter 3, I shift gears and focus on the interaction between the onset of Medicare at age 65 and mental health care utilization and mental health outcomes.[1] Using data from the National Health Insurance Survey, I examine whether the changes in health insurance coverage rates that occur at age 65 are accompanied by changes in mental health outcomes. I employ a regression discontinuity design to test for changes in perceived financial barriers to mental health care, visits with mental health professionals, and self-reported mental health. I find that the onset of Medicare at age 65 is accompanied by a substantial decline in self-reported barriers to receiving mental health care, especially among individuals with lower levels of educational attainment. However, I find no changes in visits with mental health care professionals or measures of self-reported mental health.

[1]This study was published in *The Journal of Mental Health Policy and Economics* in March 2018 (Rhodes, 2018).

CHAPTER I

Private Health Insurer Incentives and Prescription Opioid Use: Evidence from Medicare Part D

1.1 Introduction

Private health insurers play an increasingly prominent role in the provision of public health insurance benefits. Since the 1980s, Medicare beneficiaries have had the option to enroll in a private managed care plan in place of traditional fee-for-service Medicare. In the 1990s, states began contracting with private managed care organizations to deliver Medicaid benefits. Since 2006, the Medicare Part D program has provided coverage for prescription drug expenditures, with benefits administered entirely by private insurers. In recent years, both the Medicare and Medicaid programs have seen a significant increase in the percentage of beneficiaries enrolled in private plans. In 2017, nearly one-third of Medicare beneficiaries were enrolled in a private Medicare Advantage (MA) plan; 40 percent of Medicare beneficiaries were enrolled in a private stand-alone drug plan; and, 70 percent of Medicaid beneficiaries were enrolled in a private managed care plan (Gruber, 2017; Jacobson et al., 2017; KFF, 2019). The growing presence of private insurers in the Medicare and Medicaid programs has increased the importance of better understanding how these firms' incentives interact with beneficiary welfare.

In this study, I examine one channel through which private health insurer incentives

may align with improved enrollee health outcomes. Integrated health insurance plans that provide comprehensive coverage for a range of health care services have an incentive to consider the substitutability or complementarity across different modes of treatment. I test the hypothesis that integrated plans internalize externalities from prescription drugs.

I exploit the unique institutional design of the Medicare Part D prescription drug program to test my hypothesis. Broadly speaking, two types of private insurers operate in the Part D program; Medicare Advantage Part D plans (MA-PDPs), which provide comprehensive coverage for drug and non-drug expenditures, and stand-alone Part D plans (SA-PDPs), which provide coverage for prescription drugs only. Because of the breadth of coverage that they provide, MA-PDPs have an incentive to consider externalities from enrollee drug use. Conversely, SA-PDPs do not face the costs of hospital or outpatient care and have no incentive to consider these externalities.

I examine the interaction between private health insurer incentives and a class of drugs that are associated with negative externalities – prescription opioids. Because MA-PDPs face the costs of hospital care, these plans have an incentive to consider adverse health outcomes linked to opioid use. SA-PDPs do not face the costs of hospital care and have no incentive to consider these adverse health outcomes. Using a 20 percent sample of Medicare beneficiaries from 2008 through 2015, I examine whether MA-PDP enrollment affects measures of opioid use. I motivate my analysis with evidence from the medical literature on the link between high dosages of opioids and adverse health outcomes.

An empirical challenge in determining whether MA-PDP enrollment affects opioid use is that plan enrollment is non-random. There is a long history of favorable selection into MA plans; as a result, a naïve comparison of opioid use across MA-PDP enrollees and SA-PDP enrollees may capture both plan efforts to manage care, as well as unobservable differences in health status. I introduce a novel strategy to identify the causal effect of MA-PDP enrollment on measures of opioid use. My identification strategy leverages two policy changes that resulted in higher payments to Medicare Advantage (MA) plans

operating in 72 "treatment" counties relative to MA plans operating in 178 "control" counties. As a result of these higher payments, plans operating in treatment counties were motivated to enroll a greater number of Medicare beneficiaries relative to plans operating in control counties. I exploit variation in payments to MA plans operating in treatment and control counties to generate an instrument for MA-PDP enrollment that is plausibly exogenous to beneficiary health status.

I find that MA-PDP enrollment lowers the probability of opioid use by 8.4 percent relative to SA-PDP enrollment. Conditional on any opioid use, MA-PDP enrollment also lowers intensity of opioid use. In particular, I find that MA-PDP enrollment reduced the likelihood of high dosage opioid use by 32 percent in 2008 and 2009. There are several mechanisms through which MA-PDPs may have limited enrollees' use of high dosage opioids. For example, plans could have worked with providers to ensure safer prescribing levels or excluded high dosage opioids from their formularies. While I am unable to determine the exact mechanism in this study, I am examining this issue in related work. However, I find that MA-PDP enrollment lowered the probability of propoxyphene use, a high dosage opioid that was withdrawn from the market in 2010. The effect of MA-PDP enrollment on reducing propoxyphene use was the primary factor in lowering dosages during this period.

This study is most closely related to recent work by Baker et al. (2020), who also examine the impact of MA-PDP enrollment on opioid use. They find that MA-PDP enrollment lowers the probability of opioid use; however, conditional on any opioid use, they find no effect of MA-PDP enrollment on intensity of use. My analysis differs from theirs in several ways. First, our studies examine different samples of Medicare beneficiaries. My identification strategy relies on variation in payments to MA plans operating in smaller metropolitan areas. Their study exploits a discontinuous change in payments to MA plans that operate in counties that are part of larger metropolitan areas with populations of 250,000 or more. Given that my analysis focuses on beneficiaries who reside in smaller

metropolitan areas, my findings may be of particular importance to policymakers, in light of the opioid epidemic's effect on rural America.

Second, while their study focuses on opioid use during 2014, I examine opioid use during the years 2008 through 2015. This longer period of analysis allows me to test for differences in the effect of MA-PDP enrollment on measures of opioid use over time. This issue is particularly salient given the shift in the medical community's reassessment of safe opioid prescribing guidelines that occurred during these years.

Third, while their study uses opioid days supply to gauge intensity of use, I identify measures of opioid use that are associated with negative externalities. Although the use of opioids for non-cancer pain remains controversial, these drugs continue to serve as an essential treatment for pain management. I harness evidence from the medical literature on the link between high opioid dosages and adverse health outcomes to distinguish between "safe" and "dangerous" measures of opioid use.

This study adds to a growing literature that examines the interaction between private health insurer incentives and externalities from prescription drugs in the Medicare program. Both Lavetti and Simon (2018) and Starc and Town (2019) show that relative to SA-PDPs, MA-PDPs offer more generous coverage for drugs that have been shown to reduce hospitalizations. In light of a rich literature that documents price-sensitivity in the demand for prescription drugs, their findings indicate that MA-PDPs internalize positive externalities from prescription drugs. I find that MA-PDP enrollment reduces the probability of high dosage opioid use, indicating that integrated plans internalize negative externalities from prescription drugs. This finding may be of importance to policymakers as both integrated and fragmented drug plans continue to play a larger role in the administration of public health insurance benefits.

1.2 Background

1.2.1 The Medicare Part D Program

The Medicare program provides nearly universal health insurance coverage to individuals aged 65 and older and to those receiving disability insurance through the federal government. The program consists of four components, although there is significant overlap. Medicare Part A provides coverage for the costs of inpatient hospital care, while Medicare Part B provides coverage for the costs of physician and outpatient hospital care. Medicare beneficiaries have the option to obtain coverage for the services covered under Parts A and B through either a private Medicare Advantage (MA) plan or through traditional fee-for-service Medicare (TM). MA plans (formerly referred to as Part C and +Choice plans) receive a monthly per-enrollee payment from the federal government in exchange for providing coverage for the services covered under Parts A and B. Under TM, medical benefits covered under Parts A and B are administered directly by the federal government.

The fourth component of Medicare is the Part D program, which provides coverage for prescription drug expenditures. Part D benefits are administered entirely by private insurers. Broadly speaking, there are two types of plans that operate in Medicare Part D: Medicare Advantage Part D plans (MA-PDPs) and stand-alone Part D plans (SA-PDPs). MA-PDPs are integrated into parent MA plans, while SA-PDPs provide coverage for prescription drug expenditures only. The typical enrollee in an MA-PDP receives coverage for the services covered under Parts A, B, and D through a single private insurer, while the typical enrollee in an SA-PDP supplements enrollment in TM with prescription drug coverage through a private stand-alone plan.

1.2.2 Integrated Plans and Externalities

MA-PDPs and SA-PDPs face different incentives regarding externalities from prescription drugs. Because of the breadth of coverage that they provide, MA-PDPs have an incentive to consider externalities from prescription drugs into other modes of care. SA-PDPs provide coverage for prescription drugs only and have no incentive to consider these externalities. For example, if an MA-PDP enrollee requires emergency medical attention as a result of prescription opioid use, the MA-PDP would have to cover the costs of both the initial drug and the emergency care. In contrast, SA-PDPs are not responsible for emergency care and have no incentive to consider this downstream cost.

Two recent studies examine whether MA-PDPs internalize positive externalities from prescription drugs (Lavetti and Simon, 2018; Starc and Town, 2019). The analysis in these studies is motivated by the previous findings that consumers are price-sensitive in their demand for prescription drugs, and that underutilization of certain medications may lead to inpatient hospitalizations (Chandra et al., 2010; Swartz, 2010). These findings suggest that MA-PDPs have an incentive to set low cost-sharing requirements for drugs that reduce hospitalizations, to ensure that financial restrictions do not prevent enrollees from accessing these drugs. Because SA-PDPs do not face the costs of hospital care, they have no such incentive.

Both Lavetti and Simon (2018) and Starc and Town (2019) test the hypothesis that integrated plans internalize positive externalities from prescription drugs. Using Part D utilization data, Starc and Town (2019) find that MA-PDP enrollees pay 10 percent less in out-of-pocket costs than their SA-PDP counterparts for drugs used in the treatment of conditions such as asthma, diabetes, and high cholesterol. Using Part D benefit design data, Lavetti and Simon (2018) show that the out-of-pocket costs faced by MA-PDP enrollees for a similar set of "spillover drugs" are six to eight percent lower than those faced by SA-PDP enrollees. The findings from both studies suggest that MA-PDPs internalize

positive externalities from prescription drugs that may reduce hospitalizations.

In this study, I also examine whether integrated MA-PDPs internalize externalities from prescription drugs. However, I focus on a class of drugs that have been linked to negative externalities – prescription opioids. A related study by Baker et al. (2020) finds that MA-PDP enrollment reduces the likelihood of any opioid use. My analysis differs from theirs in several ways. First, relative to the sample of beneficiaries used in their analysis, my analysis focuses on beneficiaries who reside in smaller metropolitan areas. Second, while their study focuses on beneficiary opioid use during 2014, I examine beneficiary opioid use during the years 2008 through 2015. The period of analysis in my study overlaps with the height of both opioid prescribing levels and negative externalities from prescription opioid use. Third, while their study largely focuses on the effect of MA-PDP enrollment on extensive margin opioid use, my analysis focuses on the effect of MA-PDP enrollment on intensive margin measures of use. I distinguish between "safe" and "dangerous" opioid use by identifying measures of intensity of opioid use that are associated with adverse health outcomes.

1.2.3 Negative Externalities from Prescription Opioids

Prescription opioids have a complex history in the U.S. health care system. For most of the 20th century, these drugs were generally reserved for the treatment of individuals suffering from the most severe forms of pain, including post-surgical and terminal cancer patients. During this period, the medical community was generally in agreement that any benefits from opioid treatments for non-cancer pain were outweighed by the health risks associated with using these drugs, including respiratory failure and addiction. This perception began to shift in the late-1980s and into the 1990s following the designation of pain severity as a "fifth vital sign" by major medical groups, and the growing belief among physicians that pain is a debilitating condition associated with high rates of health care utilization and large costs to society (Dworkin and Sherman, 2001; Rosenblum et al.,

2008). In response, pharmaceutical companies developed an array of opioid formulations and touted these drugs as safe and effective treatments for chronic non-malignant pain (CNMP).

Efforts to address CNMP were especially salient among the elderly. This segment of the population faces high rates of chronic pain stemming from their susceptibility to conditions that become more common later in life, such as arthritis. In 2006, the Centers for Medicare and Medicaid Services (CMS) began issuing a post-discharge survey to Medicare inpatients with questions regarding the adequacy of their pain treatment. Concomitant with the growing focus on pain management was the increased acceptance, if not encouragement, of the use of prescription opioids as a preferred treatment over nonsteroidal anti-inflammatory drugs (NSAIDs) for elderly patients with CNMP (AGS, 2009). This position was echoed by the World Health Organization (WHO) in its 2008 "Analgesic Ladder Guidelines" (WHO, 2008).

The increased acceptance of opioids for the treatment of non-cancer pain was followed by a substantial rise in year-to-year opioid prescriptions. Between 1997 and 2002, the number of OxyContin prescriptions, a potent long-acting oxycodone formulation, increased from 670,000 to 6.2 million (Van Zee, 2009). By 2006, one in five adults in the United States was prescribed an opioid (Kelly et al., 2008). Between 1998 and 2006, more than three percent of elderly individuals were estimated to be regular users of these drugs (Stagnitti, 2009). The rise in opioids for medical purposes was accompanied by an increase in adverse health outcomes from opioid use, forcing the medical community to reevaluate the appropriateness of these drugs for the treatment of non-cancer pain (Rosenblum et al., 2008). In particular, a number of researchers began examining the link between opioid dosage levels and adverse health outcomes (Franklin et al., 2005; Fernandez et al., 2006).

Between 2009 and 2011, researchers established many of the safety thresholds for daily opioid dosages that continue to be recognized today. This literature documented a heightened risk of adverse health events among individuals taking daily opioid dosages

of 50 morphine milligram equivalents (MME) or more (Dunn et al., 2010; Bohnert et al., 2011). Because of their susceptibility to bone fractures, researchers found that the elderly are particularly vulnerable to the side-effects of high opioid dosages, including dizziness and sedation (Saunders et al., 2010).

The use of opioids for non-cancer pain remains controversial, and opioid prescribing guidelines emphasize the importance of considering each patient's risk profile when choosing the most appropriate treatment. Despite the complicated history of these drugs, and the ongoing opioid epidemic, opioids remain an essential treatment for pain management. However, the shift in the medical community's assessment of safe dosage prescribing levels presents an empirical framework to test the hypothesis that MA-PDPs internalize negative externalities from these drugs. MA-PDPs face the costs of hospital care and have an incentive to limit enrollee exposure to high opioid dosages, while SA-PDPs provide coverage for drug expenditures only and have no incentive to consider these negative externalities. I test for differences in measures of opioid use and dosage levels across MA-PDP and SA-PDP enrollees to determine whether MA-PDPs internalize negative externalities from these drugs.

1.3 Data and Outcomes

1.3.1 Cohort Construction

I use a 20 percent sample of Medicare beneficiaries from years 2008 through 2015 to test for differences in measures of opioid use across MA-PDP and SA-PDP enrollees. Beneficiaries are selected for inclusion in the sample if their Social Security Number ends in a zero or a five, and generally appear longitudinally across all data years in which they are enrolled. The initial sample consists of 15.3 million beneficiaries and 86.1 million observations. I exclude a small fraction of observations that contain no information on Part D enrollment. I then impose several sample restrictions to make the cohorts of MA-

PDP and SA-PDP enrollees more comparable (Table A.1). I exclude beneficiaries who do not currently, or did not originally, qualify for Medicare benefits on the basis of age (i.e. the disabled); beneficiaries who are also enrolled in Medicaid (dual-eligibles); and, Part D low-income subsidy (LIS) recipients. These restrictions remove from the analysis observations that correspond to individuals with characteristics that are likely correlated with both opioid use and plan choice in unobservable ways. For example, Medicare beneficiaries under the age of 65, who generally obtain coverage through disability status, exhibit significantly higher rates of opioid use than beneficiaries aged 65 and older (Morden et al., 2014). These individuals are also much more likely to be enrolled in an SA-PDP and to be a recipient of the LIS than their over-65 counterparts (Cubanski et al., 2016).

I also exclude from the analysis beneficiaries who are not enrolled in the same Part D plan throughout the calendar year. These beneficiaries either gain or lose Part D coverage after the start of the year, or they change plans over the course of the year. I exclude these observations for two reasons; first, because I construct measures of opioid use at the annual level, outcomes are scaled for beneficiaries with partial-year coverage. Scaling outcomes may generate erroneous values, especially for beneficiaries who either gain coverage late in the calendar year or lose coverage early in the calendar year. Second, changes in Part D coverage are generally restricted to an open enrollment period (October through December), and take effect the following year. The motivating factors for within-year changes in Part D plan enrollment are unclear. After removing observations subject to these restrictions, the remaining sample consists of 48 million observations.

I impose several additional data cleaning restrictions. I exclude beneficiaries who reside outside of the U.S.; observations with missing or unknown gender; and, beneficiaries with less than 12 months of enrollment in TM (Parts A and B) or MA during the calendar year. Following Afendulis et al. (2017), I drop observations that correspond to beneficiaries enrolled in a private fee-for-service (PFFS) plan. Historically, PFFS plans have been exempt from network requirements; as a result, these plans faced a different

set of incentives than other types of MA plans (Frakt et al., 2009).[1] Finally, I exclude observations that correspond to beneficiaries under the age of 65 or over the age of 99.

I link a large set of geographic covariates to the cohort of Medicare beneficiaries. At the county-level, I obtain information on unemployment rates from the Bureau of Labor Statistics (BLS); information on poverty rates, household income, and disability rates from the Census Bureau; and, information on population density and health care market characteristics from the Area Health Resource File. I obtain information on metropolitan and core-based statistical area populations from the Census Bureau. Finally, I obtain information on state prescription drug monitoring programs (PDMPs) from Buchmueller and Carey (2018). PDMPs collect data on prescriptions for controlled substances, including prescription opioids, to identify inappropriate prescribing levels. The final cohort consists of 7.7 million beneficiaries and 35.4 million observations.

1.3.2 Outcomes

I obtain information on prescription opioid use from the 2008 through 2015 Part D Event (PDE) files. Each observation in the PDE files represents a prescription fill. The data contain the corresponding national drug code (NDC) for each prescription, the date the prescription was filled, and the days supply of the prescription. I identify opioid drugs by NDC code, and I limit the data to entries that correspond to the list of drugs detailed in Table A.2. I link information on opioid prescription fills from the PDE data to the cohort of Medicare beneficiaries by a unique beneficiary identification number and year.

I generate four measures of opioid use at the annual level. First, I create an indicator for any opioid use during the calendar year. I next generate several measures that are intended to capture intensity of opioid use. These measures are constructed from two fields: morphine milligram equivalents (MME) and the days supply associated with each pre-

[1] I identify plan type by the "Contract ID" and "Plan ID" fields. Plan identifiers are encrypted for data year 2012; I drop 2012 beneficiaries who were enrolled in a PFFS plan at any point prior to, (2008-2011), or after, (2013-2015), 2012. The results are robust to excluding data year 2012 from the analysis.

scription. MME is a commonly employed measure that standardizes dosage levels across opioids of different ingredients, strengths, and routes of administration into equivalent milligrams of morphine. For example, 90 tablets of 10 milligrams of oxycodone has an MME of 1,350 (10*90*1.5).

I construct three measures of intensity of opioid use at the annual level from the MME and the days supply fields. First, I compute the annual daily morphine equivalent dosage (MED) for each beneficiary by dividing the sum of morphine milligram equivalents across all prescriptions used during the calendar year by the total days supply corresponding to these prescriptions. Second, I identify the maximum daily MED used during the calendar year. Third, I create an indicator for whether a prescription for 50 daily MED or more was used during the calendar year. For enrollee i in year t with n opioid prescriptions, these fields are calculated as follows:

$$AnnualDailyMED_{it} = \frac{\sum_{j=1}^{n} MME_{itj}}{\sum_{j=1}^{n} DaysSupply_{itj}} \tag{1.1}$$

$$MaxDailyMED_{it} = max\Big\{\frac{MME_{it1}}{DaysSupply_{it1}}, \frac{MME_{it2}}{DaysSupply_{it2}}, ..., \frac{MME_{itn}}{DaysSupply_{itn}}\Big\} \tag{1.2}$$

$$AnyDailyMED_{it} \geq 50 = \mathbf{1}\Big\{MaximumDailyMED_{it} \geq 50\Big\} \tag{1.3}$$

The annual daily MED field captures average opioid dosages throughout the calendar year, while the maximum daily MED and 50 or more daily MED fields capture individual prescriptions that correspond to high dosages. For example, a beneficiary with three opioid prescriptions corresponding to 20, 30, and 70 daily MED (with equivalent days supply) has annual daily MED use of 40, maximum daily MED use of 70, and is flagged for using a prescription for 50 daily MED or more.

1.4 Empirical Strategy

An empirical challenge in using Part D utilization data to determine whether MA-PDPs internalize negative externalities from prescription opioids is that plan enrollment is non-random. There is a long history of favorable selection into MA plans; while there is evidence that this has declined in recent years, plans continue to attract healthier enrollees to increase profit margins (McWilliams et al., 2012; Brown et al., 2014). This issue is particularly salient when examining prescription opioids, as opioid use is strongly correlated with poorer health status (Cicero et al., 2009). As a result, a naïve estimate of opioid use on MA-PDP enrollment will capture both differences in underlying health status across enrollees, as well as any efforts by MA-PDPs to internalize negative externalities from these drugs. I develop an instrument for MA-PDP enrollment that is plausibly exogenous to beneficiary health status. I construct this instrument from two sources of policy variation: county benchmark payment floors to MA plans and the 2000 reclassification of metropolitan America.

1.4.1 County Benchmark Payment Floors

MA plans receive a monthly, per-enrollee payment from the federal government in exchange for providing coverage for the services covered under Parts A and B. These payments are calculated from two inputs: legislatively determined county benchmark amounts and an enrollee-specific risk-adjustment factor. County benchmark amounts are based on the level of lagged Medicare spending for the population of TM enrollees residing within an MA plan's county of operation. This amount is then scaled by an individualized beneficiary risk score that adjusts for demographic characteristics and health status. The per-enrollee payment thus functions to capture local health care spending levels through the benchmark amount, and to disincentive MA plans from actively seeking to attract healthier beneficiaries through the individualized risk score.

In an effort to increase MA presence in areas with historically low TM spending levels (in particular, rural areas) the federal government introduced a county benchmark floor of $367 in January 1998 (Table 1.1, Figure A.1). Beginning in March 2001, the government authorized a second benchmark payment floor that set a 10.5 percent premium on the original (inflation-adjusted) payment floor; however, the higher payment floor applied only to MA plans operating in counties that were part of metropolitan statistical areas (MSAs) with populations of 250,000 or more. The second payment floor is often referred to as the "urban floor," as it was intended to increase MA presence in more populated metropolitan areas.

1.4.2 The Reclassification of Metropolitan America

In 2000, the Office of Management and Budget (OMB) introduced a new classification system for defining metropolitan America. The new system was designed to account for changes in economic, commuting, and settlement patterns that had taken place since the agency was first tasked with designating metropolitan areas in the 1940s (Frey et al., 2004). The new system introduced the concept of core based statistical areas (CBSAs) and categorized these areas as "metropolitan" or "micropolitan." In 2003, OMB issued its first listing of areas defined under the new classification system and advised federal agencies to employ the more recent statistical definitions when conducting research and implementing policy. CMS adopted these new definitions for use in assigning county benchmark amounts beginning in March 2004 (Table 1.1, Figure A.3).

The conversion to the new classification system significantly altered the composition of metropolitan areas designated by OMB. For the majority of counties that were part of MSAs under the old classification system, the conversion to the new classification system had no effect on urban floor status; these counties did not shift across the 250,000-population threshold (Table 1.2, Figure 1.1). However, 72 counties that were part of MSAs with populations above 250,000 became part of CBSAs with populations below

this threshold. These counties were grandfathered into urban floor status. As a result, plans operating in these counties continued to be subject to the higher floor amount in March 2004. Had CMS introduced the urban floor in March 2004 instead of March 2001, plans operating in these counties would not have been subject to the higher floor amount.

1.4.3 Counties of Analysis

I focus the analysis in this study on Medicare beneficiaries who reside in two types of counties: "never urban" counties and "reclassified" counties (Table 1.2). Both never urban and reclassified counties were part of MSAs under the old metropolitan classification system, and these counties became part of CBSAs with populations below 250,000 under the new metropolitan classification system. However, under the old classification system, never urban counties were part of MSAs with populations below this threshold, while reclassified counties were part of MSAs with populations above this threshold. Although never urban and reclassified counties are part of CBSAs with similar populations, reclassified counties were grandfathered into urban floor status. As a result, plans operating in reclassified counties continued to be subject to a higher payment floor than their never urban counterparts.

Table 1.3 presents examples of never urban and reclassified counties. Webster Parish, Louisiana is an example of a reclassified county. In 1999, Webster Parish was part of the Shreveport-Bossier City MSA. Because the Shreveport-Bossier City MSA had a population of 377,673 under the old metropolitan classification system, MA plans operating in Webster Parish were subject to the higher urban floor benchmark amount of $525 beginning in March 2001. Under the new metropolitan classification system, Webster Parish became part of the Minden, Louisiana micropolitan statistical area. Although the Minden, Louisiana micropolitan statistical area had a population of 41,814 in March 2004, well below the 250,000-population threshold, Webster Parish was grandfathered into urban floor status. Auglaize, Ohio is an example of a never urban county. In 1999, Auglaize was part

of the Lima MSA, with a corresponding population of 154,065. In 2003, Auglaize became part of the Wapakoneta micropolitan statistical area, with a corresponding population of 46,230. Although Webster Parish and Auglaize were part of micropolitan statistical areas with similar populations in March 2004, plans operating in Webster Parish were subject to the higher urban floor amount while plans operating in Auglaize were subject to the lower floor amount.

Table 1.4 presents summary statistics for the full cohort of Medicare beneficiaries, as well as the sample of beneficiaries in never urban and reclassified counties. Never urban and reclassified counties differ from the full cohort of counties in several observable ways: these counties have a higher percentage of white beneficiaries, smaller populations, lower household incomes, lower 2004 FFS spending levels, and, by design, are part of CBSAs with smaller populations. Beneficiaries in never urban and reclassified counties are also more likely to reside in the Midwest and the South.

Never urban and reclassified counties are similar in many respects and where there are significant differences there is no clear pattern. Relative to never urban counties, reclassified counties have a higher percentage of white beneficiaries, lower poverty rates, and are more likely to be located within a state with any PDMP law in effect during the sample years. Reclassified counties also have higher corresponding benchmark amounts; this $52 difference is expected, given the difference in payment floors across never urban and reclassified counties. The higher benchmark amounts that correspond to reclassified counties are associated with higher rates of MA, MA-PDP, and Part D enrollment.

Table 1.5 presents summary statistics for the subsample of Medicare beneficiaries with Part D coverage. Conditional on having Part D coverage, benchmark amounts corresponding to reclassified counties remain higher, on average, than benchmark amounts corresponding to never urban counties. Higher benchmark amounts again coincide with higher rates of MA and MA-PDP enrollment in reclassified counties.

1.4.4 Excess Payments to MA Plans Instrument

I exploit differences in benchmark amounts across never urban and reclassified counties to develop an instrument for MA-PDP enrollment. The benchmark amount is determined by county average FFS spending levels and payment floors; the benchmark amount is set at the payment floor for counties with average FFS spending levels below the floor amount, and at the average FFS spending level for counties with average FFS spending above the floor amount. Figure 1.2 presents the relationship between average FFS spending levels and payment floors across never urban and reclassified counties in March 2004. The benchmark amount for counties with average FFS spending above the higher floor is set at the level of average FFS spending for both never urban and reclassified counties. The benchmark amount for counties with average FFS spending between the two payment floors varies across never urban and reclassified counties: the benchmark amount is set at the level of average FFS spending for never urban counties, and at the higher (urban) floor amount for reclassified counties. The benchmark amount for counties with average FFS spending below the lower floor amount is set at the lower floor amount for never urban counties, and at the higher floor amount for reclassified counties.

I construct a measure of "excess payments" to plans that operate in reclassified counties. This measure captures the difference in benchmark payments to plans that operate in never urban and reclassified counties with the same levels of average FFS spending. Figure 1.3 illustrates the variation in this measure. For counties with average FFS spending levels above the higher payment floor, the difference in benchmark amounts across never urban and reclassified counties is \$0. For counties with average FFS spending levels between the two payment floors, the difference in benchmark amounts between never urban and reclassified counties is the difference between the higher floor amount and average FFS spending. For example, a plan operating in a reclassified county with average FFS spending of \$600 will receive an excess payment of \$13.89 relative to a plan operating

in a never urban county with the same level of average FFS spending ($613.89 − $600). For counties with average FFS spending below the lower floor amount, the difference in benchmark payments across never urban and reclassified counties is fixed at the difference between the two payment floors ($58.47).

The excess payments measure effectively designates never urban counties as the counterfactual for what would have occurred in reclassified counties in the absence of the urban floor. The higher payments to MA plans that operate in reclassified counties are driven by the intersection of two policy changes – the urban floor and the reclassification of metropolitan America – and do not reflect underlying differences in beneficiary health status across never urban and reclassified counties. I harness variation in the excess payment measure to instrument for MA-PDP enrollment. The per-enrollee payments that plans receive from the federal government are expected to cover the costs of beneficiary care. Excess payments increase the likelihood that plans will generate a profit on a given enrollee and motivate plans to enroll a greater number of beneficiaries. Figure 1.4 illustrates the positive correlation between excess payments to MA plans and MA penetration rates.

My identification strategy hinges on the assumption that residence in a reclassified county is uncorrelated with opioid use, except through its effect on MA-PDP enrollment. One concern is that designation as a reclassified county in 2004 was the result of changing economic or population patterns. For example, reclassified counties could have become economically detached from larger metropolitan areas in ways that are correlated with opioid use. The history and implementation of OMBs new metropolitan classification system suggest that this is not the case. First, the core-based approach relied on methodology and population estimates from the year 2000, one year prior to the introduction of the urban floor. Second, counties that went from being part of more populated MSAs under the old classification system to being part of smaller CBSAs under the new classification system did so because of "a more stringent commuting threshold" requirement,

rather than changing demographic or socioeconomic patterns (Frey et al., 2004). Third, the introduction of the new metropolitan standards followed a decade-long effort by OMB; reclassified counties were likely comparable to their never urban counterparts well-before the 2000 issuance of the new standards and the 2003 release.

Previous studies have employed a regression discontinuity (RD) analysis that exploits the 250,000 population threshold to identify the causal effect of MA and MA-PDP enrollment on the use of health care services and health outcomes (Afendulis et al., 2017; Baker et al., 2020). Although conceptually similar, my instrumental variables strategy, which is identified entirely by non-urban counties, offers a potential advantage over the RD approach. The discontinuity analysis relies heavily on functional form and bandwidth assumptions about the running variable – CBSA population. The IV approach that I propose does not require these assumptions; by design, never urban and reclassified counties are part of CBSAs with similar populations, and treatment status is not determined by this field. Furthermore, my results are not sensitive to the inclusion of the CBSA population field in the analysis.

1.4.5 Methods

To determine the impact of MA-PDP enrollment on opioid use, I begin by estimating the following specification across the sample of beneficiaries in never urban and reclassified counties:

$$Y_{ic_{(s,r)}t} = \beta_0 + \beta_1 MAPD_{it} + \beta_2 \mathbf{X}_{it} + \beta_3 \mathbf{V}_{ct} + \beta_4 \mathbf{Z}_{st} + \theta_r + \gamma_t + \epsilon_{ic_{(s,r)}t} \tag{1.4}$$

$Y_{ic_{(s,r)}t}$ represents measures of opioid use for enrollee i residing in county c (in state s and region r) in year t. In addition to any opioid use, I examine the impact of MA-PDP enrollment on intensity of use. I estimate the logarithmic transformation of annual

daily MED use and maximum daily MED use; Box-Cox tests favor the log specifications over the linear specifications, with a parameter estimate of 0.14 corresponding to annual daily MED use and an estimate of 0.05 corresponding to maximum daily MED use. $MAPD_{it}$ is an indicator for whether beneficiary i is enrolled in an MA-PDP in year t. β_1 is the coefficient of interest and captures the average treatment effect (ATE) of enrollment in an MA-PDP relative to enrollment in an SA-PDP. The terms $\mathbf{X}_{it}$, $\mathbf{V}_{ct}$, and $\mathbf{Z}_{st}$ represent vectors of covariates that may be correlated with MA-PDP enrollment and opioid use. The term $\mathbf{X}_{it}$ represents a vector of time-varying and time-invariant individual characteristics, including age, gender, and race. The term $\mathbf{V}_{ct}$ represents a vector of time-varying and time-invariant county characteristics, including disability rate, poverty rate, unemployment rate, local health care market characteristics, 2004 average FFS spending levels, and the corresponding CBSA population. The term $\mathbf{Z}_{st}$ controls for a vector of time-varying state covariates, including any PDMP law in effect and a must access PDMP law in effect. The specification includes region fixed effects that capture time-invariant regional characteristics (θ_r) and year fixed-effects that control for year-specific shocks (γ_t). Standard errors are clustered at the county-level. I estimate all models via ordinary least squares (OLS).

Given the long history of favorable selection into MA plans, enrollment in an MA-PDP may be correlated with unobserved beneficiary health status. As a result, β_1 from Equation 1.4 will capture both the effect of MA-PDP enrollment on opioid use, as well as differences in underlying health status across MA-PDP and SA-PDP enrollees. I estimate the following instrumental variables specifications to isolate the causal effect of MA-PDP enrollment on measures of opioid use:

$$MAPD_{ic_{(s,r)}t} = \alpha_0 + \alpha_1 ExcessPayments_{c,2004} + \alpha_2 \mathbf{X}_{it} + \alpha_3 \mathbf{V}_{ct} + \alpha_4 \mathbf{Z}_{st} + \theta_r + \gamma_t + \epsilon_{ic_{(s,r)}t} \quad (1.5)$$

$$Y_{ic_{(s,r)}t} = \beta_0 + \beta_1 \widehat{MAPD}_{it} + \beta_2 \mathbf{X}_{it} + \beta_3 \mathbf{V}_{ct} + \beta_4 \mathbf{Z}_{st} + \theta_r + \gamma_t + \epsilon_{ic_{(s,r)}t} \quad (1.6)$$

The first-stage equation models the relationship between MA-PDP enrollment and 2004 excess benchmark payments to MA plans. α_1 represents the impact of a \$1 increase in excess benchmark payments to MA plans on the probability of MA-PDP enrollment. I use excess payments from 2004 for two reasons. First, the urban floor may have affected average FFS spending levels in later years. Second, after 2004 payment floors were no longer in effect; however, benchmark amounts after 2004 were adjusted according to the March 2004 levels (Figures A.3, A.4, and A.5). This meant that floor counties effectively maintained floor status if their average FFS spending levels remained below the growth-adjusted 2004 floor amounts.

Equation 1.6 models the relationship between measures of opioid use and the predicted probability of enrollment in an MA-PDP from Equation 1.4. β_1 is the coefficient of interest, and captures the local average treatment effect (LATE) of enrollment in an MA-PDP on measures of opioid use among beneficiaries who enroll in an MA-PDP as a result of excess benchmark payments to MA plans in their counties of residence. I estimate all models via two-stage least squares (2SLS), and I cluster standard errors at the county-level.

1.5 Results

1.5.1 First Stage: The Effect of Excess Payments to MA Plans on MA-PDP Enrollment

I begin by examining the strength of excess benchmark payments to MA plans in predicting MA-PDP enrollment. In Table 1.6, I present estimates of α_1 from Equation 1.5 and corresponding F-statistics from models that gradually include additional covariates. Excess payments to MA plans are a strong predictor of enrollment in an MA-PDP. In the most parsimonious model that excludes all other covariates, a $10 increase in excess payments to MA plans is associated with a 2.6 percentage point increase in the probability of enrollment in an MA-PDP. The corresponding F-statistic of 27.04 indicates that there is no weak instruments problem. Estimates of α_1 and F-statistics are generally stable in magnitude and precision across models that include additional covariates.

I also examine the strength of excess payments to MA plans in predicting MA-PDP enrollment among the subset of beneficiaries with Part D coverage. Because I observe prescription opioid use through the Part D program only, estimates pertaining to the sample of Part D enrollees constitute the true first-stage effect. The estimate from the most parsimonious model indicates that a $10 increase in excess payments is associated with a 3.6 percentage point increase in the probability of enrollment in an MA-PDP among beneficiaries with Part D coverage. The F-statistic of 36.39 exceeds the corresponding F-statistic from the sample of all beneficiaries (27.04). The inclusion of additional covariates again has minimal impact on the magnitude and the precision of the estimates.

I next examine the strength of excess payments to MA plans in predicting additional coverage outcomes, including enrollment in an MA plan and Part D enrollment (Table 1.7). Not surprisingly, estimates of α_1 are similar in magnitude across models in which MA enrollment and MA-PDP enrollment are outcomes. Excess payments to MA plans also predict Part D enrollment, which includes enrollment in either an MA-PDP or an

SA-PDP; a $10 increase in excess payments is associated with a 0.84 percentage point increase in the probability of having Part D coverage. This indicates that excess payments to MA plans increase the likelihood that two types of beneficiaries enroll in an MA-PDP: beneficiaries who would have enrolled in an SA-PDP, and beneficiaries who would not have had Part D coverage.

While I observe opioid use among beneficiaries who gain Part D coverage because of excess payments to MA plans, I do not observe opioid use among beneficiaries without Part D coverage who would have enrolled in an MA-PDP had they resided in counties with excess payments to MA plans. Previous research finds that Medicare beneficiaries who forego Part D coverage have low expected prescription drug expenditures (Levy and Weir, 2009). If beneficiaries who gain Part D coverage have low prescription drug use, estimates of β_1 may overstate the effect of MA-PDP enrollment on reducing measures of opioid use.

I test the sensitivity of my results to Part D selection by examining the impact of MA-PDP enrollment on measures of opioid use across two additional populations of Medicare beneficiaries. First, I compare estimates pertaining to the sample of all Part D enrollees against estimates pertaining to the sample of beneficiaries with chronic conditions, including diabetes, high cholesterol, and high blood pressure. I assume that beneficiaries with chronic conditions are unlikely to forego Part D coverage because they have expected prescription drug expenditures; as a result, excess payments to MA plans will not predict Part D enrollment among these beneficiaries. I flag prescription fills for antidiabetic medications, beta blockers, and statins in the Part D utilization data to identify beneficiaries with chronic conditions. Second, I examine the impact of MA-PDP enrollment on opioid use across all Medicare beneficiaries by imputing zero opioid use among beneficiaries without Part D coverage. While it is implausible to assume that all beneficiaries without Part D coverage do not use prescription opioids, these estimates provide a lower bound on the extent to which MA-PDP enrollment reduces opioid use.

1.5.2 The Impact of MA-PDP Enrollment on Any Opioid Use

In Table 1.8, I present OLS and IV estimates of β_1 from models that examine the impact of MA-PDP enrollment on the probability of any opioid use. I present estimates pertaining to the sample of all Part D enrollees, estimates pertaining to the subsample of Part D enrollees with a chronic condition, and estimates pertaining to the sample of all Medicare beneficiaries. Column 1 contains the mean rate of opioid use among beneficiaries in never urban and reclassified counties; column 2 contains the OLS estimate of β_1 from Equation 1.4; column 3 contains the IV estimate of β_1 from Equation 1.6; and, column 4 contains the p-value from a robust test of exogeneity, where the null hypothesis is that MA-PDP enrollment is exogenous to beneficiary opioid use (Wooldridge, 1995).

The estimates pertaining to the sample of all Part D enrollees indicate that MA-PDP enrollment lowers the probability of any opioid use. The OLS and the IV estimates are similar in magnitude, and I fail to reject the null hypothesis that MA-PDP enrollment is exogenous. The OLS estimate indicates that, on average, MA-PDP enrollment lowers the probability of opioid use by 2.6 percentage points; this constitutes an 8.4 percent decline from the mean rate of 31 percent. This effect is significantly lower than the 37 percent reduction documented by Baker et al. (2020).

The estimates pertaining to the subsample of Part D enrollees with a chronic condition also indicate that MA-PDP enrollment reduces the probability of opioid use. However, these estimates are smaller in both magnitude and percentage terms than the estimates pertaining to the sample of all Part D enrollees. The OLS estimate indicates that enrollment in an MA-PDP reduces the probability of opioid use by 2.1 percentage points among beneficiaries with chronic conditions; this constitutes a 6.1 percent reduction from the mean rate of 34 percent. The IV estimate is smaller in magnitude than the OLS estimate and imprecise. I again fail to reject the null hypothesis of exogeneity.

Among the sample of all Medicare beneficiaries, MA-PDP enrollment increases the

probability of opioid use. The OLS estimate indicates that MA-PDP enrollment increases the probability of opioid use by 9.9 percentage points; this represents a 49 percent increase from the mean rate of opioid use (20.2 percent). The IV estimate is similar in magnitude to the OLS estimate and precisely estimated, and I again fail to reject the null of exogeneity.

1.5.3 The Impact of MA-PDP Enrollment on Intensity of Use

In Table 1.9, I present OLS and IV estimates of β_1 from models in which measures of intensity of opioid use are outcomes. Columns 1-4 correspond to models in which the outcome is the natural logarithm of annual daily MED use; columns 5-8 correspond to models in which the outcome is the natural logarithm of maximum daily MED use; and, columns 9-12 correspond to models in which the outcome is an indicator for use of an opioid prescription with a daily MED of 50 or more. I present estimates pertaining to the sample of all Part D enrollees as well as estimates pertaining to the subsample of Part D enrollees with a chronic condition.

Among the sample of all Part D enrollees, MA-PDP enrollment lowers both annual daily MED use and maximum daily MED use. The OLS estimate in column 2 indicates that MA-PDP enrollment lowers annual daily MED use by 1.6 percent (exp(-0.0157)-1)*100), and the OLS estimate in column 6 indicates that MA-PDP enrollment lowers maximum daily MED use by 2.8 percent. While the corresponding IV estimates are both larger in magnitude than the OLS estimates, the IV estimates are imprecise. I fail to reject the null hypothesis that MA-PDP enrollment is exogenous in both models.

The OLS estimate in column 10 indicates that MA-PDP enrollment lowers the probability of using an opioid prescription with a corresponding daily MED of 50 or more by 1.5 percentage points. This represents a 4.9 percent reduction from the overall mean of 31 percent. Although the IV estimate is positive in sign, this estimate is noisy and I am unable to rule out large effects in either direction. I again fail to reject the null hypothesis that MA-PDP enrollment is exogenous.

The OLS and IV estimates pertaining to the subsample of Part D enrollees with chronic conditions are remarkably similar to the estimates pertaining to the sample of all Part D enrollees. This finding suggests that the estimates pertaining to the sample of all Part D enrollees are not biased due to Part D selection.

1.6 Sensitivity Analyses

1.6.1 The Effect of MA-PDP Enrollment on Opioid Use Over Time

Data years 2008 through 2015 represent a period of significant transition in the medical community's assessment of safe opioid prescribing practices. During this time, researchers established many of the dosage thresholds linked to adverse health outcomes that continue to be recognized today (Dunn et al., 2010; Bohnert et al., 2011). In Figure 1.6, I present average measures of opioid use throughout the data years for the full sample of Part D enrollees as well as the sample of Part D enrollees in never urban and reclassified counties. While beneficiaries in never urban and reclassified counties consistently exhibit higher levels of opioid use, both groups trend similarly. Notably, both the full sample of beneficiaries and the sample of beneficiaries in never urban and reclassified counties exhibit a significant decline in measures of intensity of opioid use between 2010 and 2011. I examine whether MA-PDP enrollment had a differential effect on opioid use throughout the sample period.

I first test the strength of excess payments to MA plans in predicting MA-PDP enrollment throughout the sample period. In Table A.3, I present estimates of α_1 that correspond to individual data years. The table contains estimates from the sample of all Part D enrollees, as well as estimates from the sample of Part D enrollees with any opioid use. I find that excess payments are a strong predictor of MA-PDP enrollment across both populations of beneficiaries throughout the sample period.

In Table A.4, I present estimates of β_1 from models that examine the impact of MA-

PDP enrollment on the probability of any opioid use throughout the sample period. These estimates are also presented in panel A of Figure 1.7. The OLS estimates corresponding to individual data years indicate that enrollment in an MA-PDP is consistently associated with lower rates of opioid use. The IV estimates are generally similar in magnitude, although these estimates are imprecise. Across all data years, I fail to reject the null hypothesis of exogeneity.

In Table A.5, I present estimates of β_1 from models that examine the impact of MA-PDP enrollment on intensity of opioid use over time. These estimates are also presented in Panels B.-D. of Figure 1.7. While both the OLS and IV estimates generally indicate that MA-PDP enrollment lowered intensity of opioid use throughout the sample period, there are several discrepancies. First, the IV estimates pertaining to years 2008 and 2009 are substantially larger in magnitude than the corresponding OLS estimates. I reject the null hypothesis of exogeneity for five out of six outcomes during these sample years. After 2009, the OLS estimates are negative and generally significant at conventional levels, while the IV estimates vary in sign and are generally imprecise. The OLS estimates suggest that MA-PDP enrollment reduced intensity of opioid use early in the sample years (2008 through 2010) and later in the sample years (2013 through 2015).

1.6.2 Instrument Validity

Although I generally fail to reject the null hypothesis of exogeneity, this test relies on the assumption that excess payments to MA plans are a valid instrument for MA-PDP enrollment. I probe the validity of the instrument by comparing IV estimates from models that gradually include additional covariates. Table A.6 presents estimates from models in which the outcome is any opioid use. The IV estimates are somewhat sensitive to the inclusion of additional covariates; this finding is expected, given the presence of Part D selection. Tables A.7, A.8, and A.9 present IV estimates from models in which the outcomes are measures of intensity of opioid use. The inclusion of additional covariates

in these models has minimal effect on the estimates, especially those pertaining to sample years 2008 and 2009.

1.7 Propoxyphene Case Study

Managed care plans that contract with the Medicare program have several tools at their disposal to influence beneficiary opioid use. For example, plans can coordinate with providers to prescribe safer dosages to plan enrollees. Plans may also avoid contracting with providers who are more prone to riskier opioid prescribing patterns. Alternatively, plans may attempt to limit enrollee exposure to high dosage opioids through benefit design. I am examining these mechanisms in related work. However, in this section I show one channel through which plans were able to limit enrollee use of high dosage opioids.

To the extent that MA-PDPs internalize negative externalities from prescription opioids, these plans will have a greater incentive to limit enrollee exposure to drugs that are more frequently linked to adverse health outcomes. In this section, I examine whether MA-PDP enrollment reduced the likelihood of propoxyphene use in 2008 and 2009.

First introduced in 1957, propoxyphene was sold under the brand names Darvon and Darvocet. Propoxyphene was popular among Medicare beneficiaries; in 2008, roughly one-quarter of Part D enrollees with any opioid use filled a prescription for propoxyphene (Figure 1.8 panel A). Despite the drug's popularity, the medical community was largely in agreement that the risks associated with propoxyphene use far outweighed any potential benefits; propoxyphene was found to be ineffective in addressing pain and its use was accompanied by substantial heart risks and a high risk of overdose (Wilson, 2010). In November 2010, following a 32-year petition, the FDA removed propoxyphene from the market. The withdrawal of propoxyphene had a significant impact on reducing intensity of opioid use among Medicare beneficiaries (Figure 1.8 panels B.-D.). In 2008 and 2009,

over 60 percent of propoxyphene users had a prescription for 50 daily MED or more; after 2010, this figure declined to less than 30 percent.

In Table 1.10, I present OLS and IV estimates of the impact of MA-PDP enrollment on the probability of propoxyphene use, as well as intensity of opioid use in 2008 and 2009. I examine the impact of MA-PDP enrollment on two populations of Medicare beneficiaries: opioid users and opioid users who did not use propoxyphene. Among opioid users, MA-PDP enrollment reduced the probability of propoxyphene use by 19 percentage points, a 76 percent reduction from the mean rate (25 percent). Enrollment in an MA-PDP also lowered intensity of opioid used during this period. Conditional on any propoxyphene use, enrollment in an MA-PDP lowered the probability of using a prescription with a daily MED of 50 or more by 14 percentage points, a 32 percent reduction from the overall rate (43 percent). Among opioid users who did not use propoxyphene, MA-PDP enrollment had a lesser effect on intensity of use.

1.8 Discussion

This study adds to a growing literature that examines the interaction between private health insurer incentives and externalities from prescription drugs. I exploit the unique institutional design of the Medicare Part D program to test the hypothesis that integrated MA-PDPs internalize negative externalities from prescription opioids. I find evidence that supports this hypothesis; relative to enrollment in a stand-alone drug plan, enrollment in an integrated MA-PDP lowered the probability of high dosage opioid use during the years 2008 and 2009. This effect was primarily the result of MA-PDP enrollment reducing the probability of propoxyphene use, a high dosage opioid that was withdrawn from the market in 2010.

The findings from this study differ from recent work by Baker et al. (2020). They find that MA-PDP enrollment reduces the probability of any opioid use; however, they find no

evidence of an effect of MA-PDP enrollment on intensity of opioid use. There are several reasons why our results may differ. First, I test for differences in measures of opioid use across beneficiaries who reside in counties that are part of smaller metropolitan areas. Their results are specific to beneficiaries who reside in counties that are part of larger metropolitan areas with a population of 250,000. The impact of MA-PDP enrollment on opioid use may vary across metropolitan areas with different populations.

Second, while their study focuses on beneficiary opioid use from 2014, my analysis spans 2008 through 2015. The years 2008 through 2015 represent a period of significant transition in the medical community's assessment of safe opioid prescribing guidelines. I find that the effect of MA-PDP enrollment on lowering measures of intensity of opioid use is most pronounced in 2008 and 2009, prior to the start of their sample period.

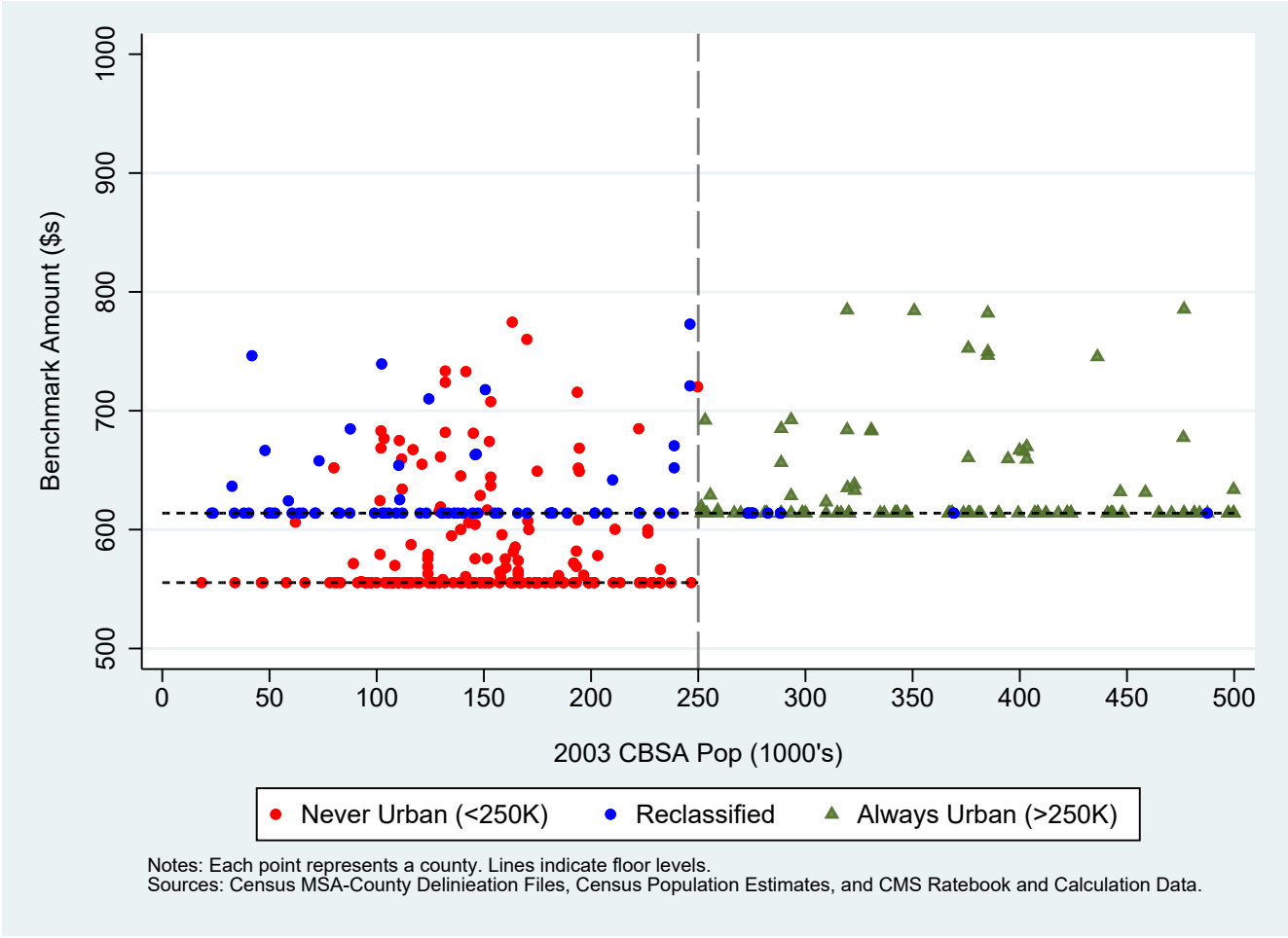
Third, while both of our studies find that MA-PDP enrollment lowers the probability of any opioid use, I document a substantially smaller effect (8 percent versus 27 percent). I find that higher benchmark payments to MA plans increase the likelihood of Part D enrollment. In sensitivity analysis, I find evidence that beneficiaries who gain Part D coverage are less likely to use opioids. This finding aligns with previous research documenting low expected drug costs among Medicare beneficiaries without Part D coverage (Levy and Weir, 2009). While the identification strategy that I employ differs from that used in Baker et al. (2020), both of our approaches rely on variation in benchmark payments to MA plans. Their finding that MA-PDP enrollment reduces the probability of opioid use may be sensitive to Part D selection.

Although I find evidence that MA-PDP enrollment lowered the probability of high dosage opioid use in 2008 and 2009, I am unable to identify how plans achieved this outcome. I am investigating this mechanism in related work. However, the finding that enrollment in an MA-PDP reduced the probability of propoxyphene use suggests that plans focused on restricting specific drugs, rather than dosages across all opioid drugs.

1.9 Conclusion

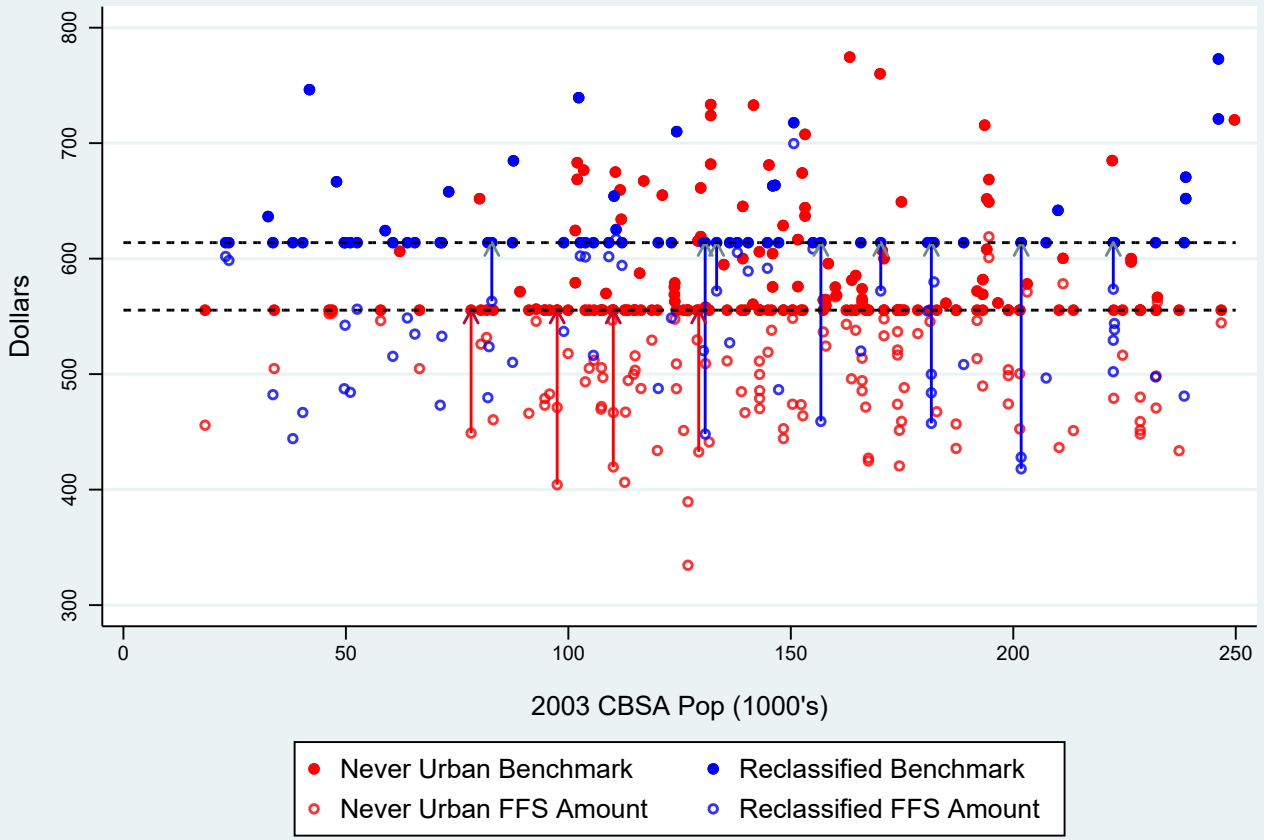
Although the Medicare program is publicly financed, private health insurers play an increasingly prominent role in the administration of Medicare benefits. Understanding how these firms' incentives interact with beneficiary welfare is of first order concern. This issue is particularly salient as the population of Medicare beneficiaries is expected to increase substantially in upcoming years. I find evidence that aligning these firms' incentives with enrollee health outcomes affects the administration of benefits.

Figure 1.1: County Benchmark Amounts for March 2004



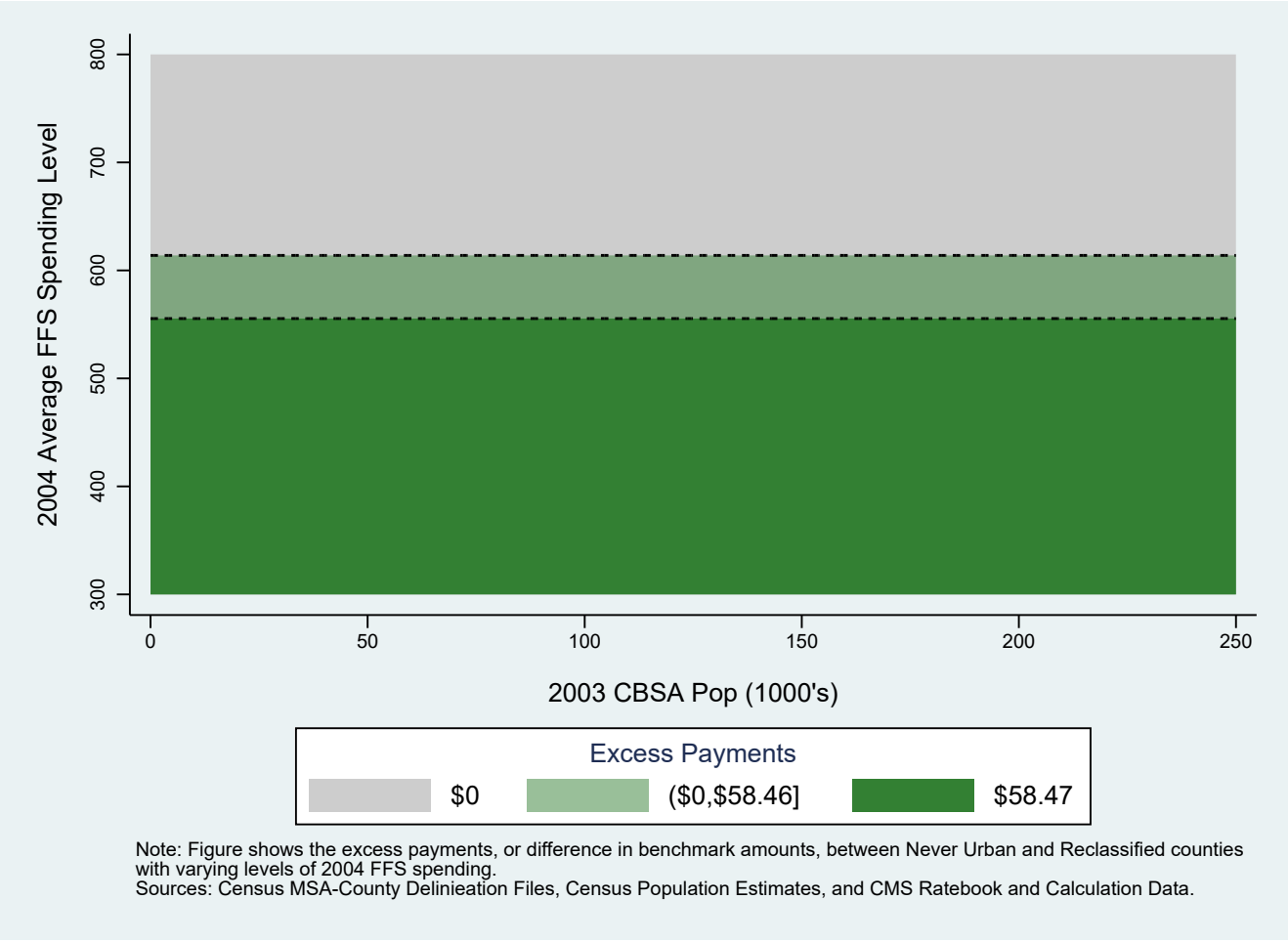
Notes: Each point represents a county. Lines indicate floor levels.
Sources: Census MSA-County Delinieation Files, Census Population Estimates, and CMS Ratebook and Calculation Data.

Figure 1.2: The Impact of Payment Floors on Benchmark Amounts in March 2004



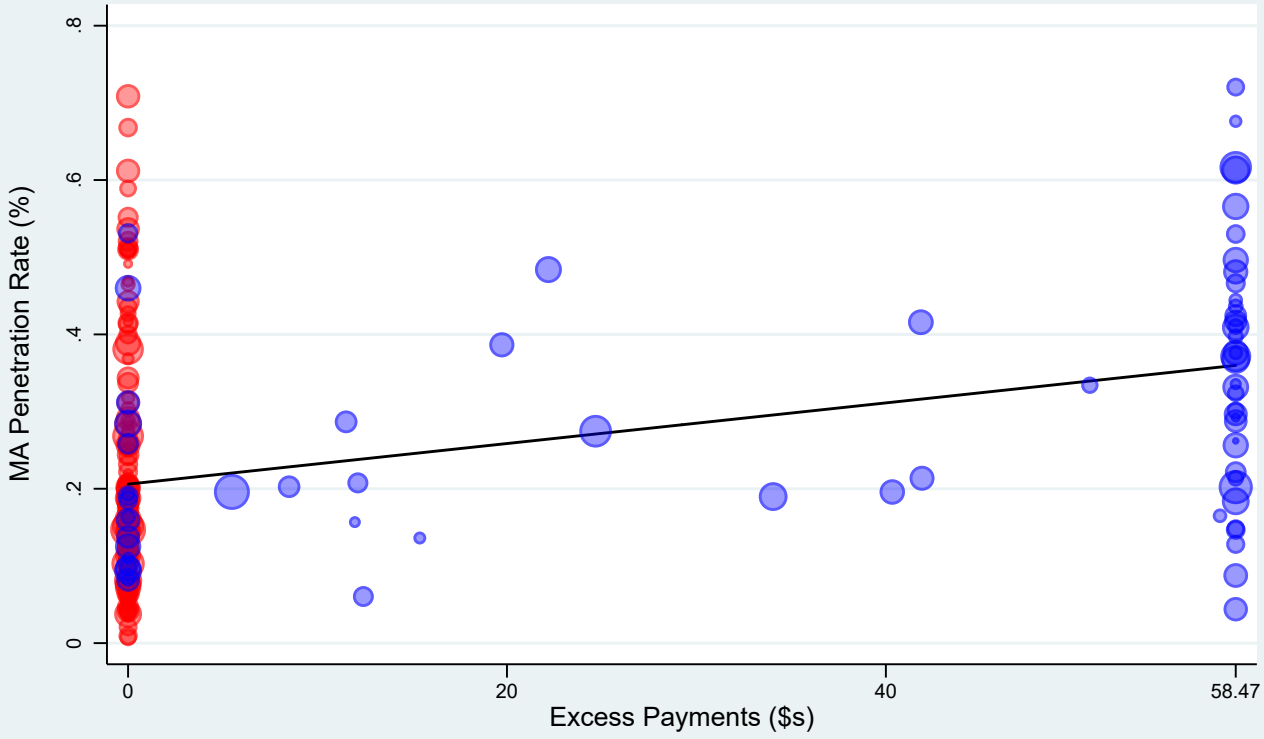
Note: Figure shows the differential effect of payment floors on benchmark amounts across Never Urban and Reclassified counties.
Sources: Census MSA-County Delinieation Files, Census Population Estimates, and CMS Ratebook and Calculation Data.

Figure 1.3: Excess Payments to MA Plans Operating in Reclassified Counties in March 2004



Note: Figure shows the excess payments, or difference in benchmark amounts, between Never Urban and Reclassified counties with varying levels of 2004 FFS spending.
Sources: Census MSA-County Delinieation Files, Census Population Estimates, and CMS Ratebook and Calculation Data.

Figure 1.4: The Association Between Excess Payments to MA Plans and MA Penetration Rates



Note: Each point represents a county, scaled by the total number of Medicare enrollees. Figure includes a linear best fit line.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Figure 1.5: Map of Never Urban and Reclassified Counties

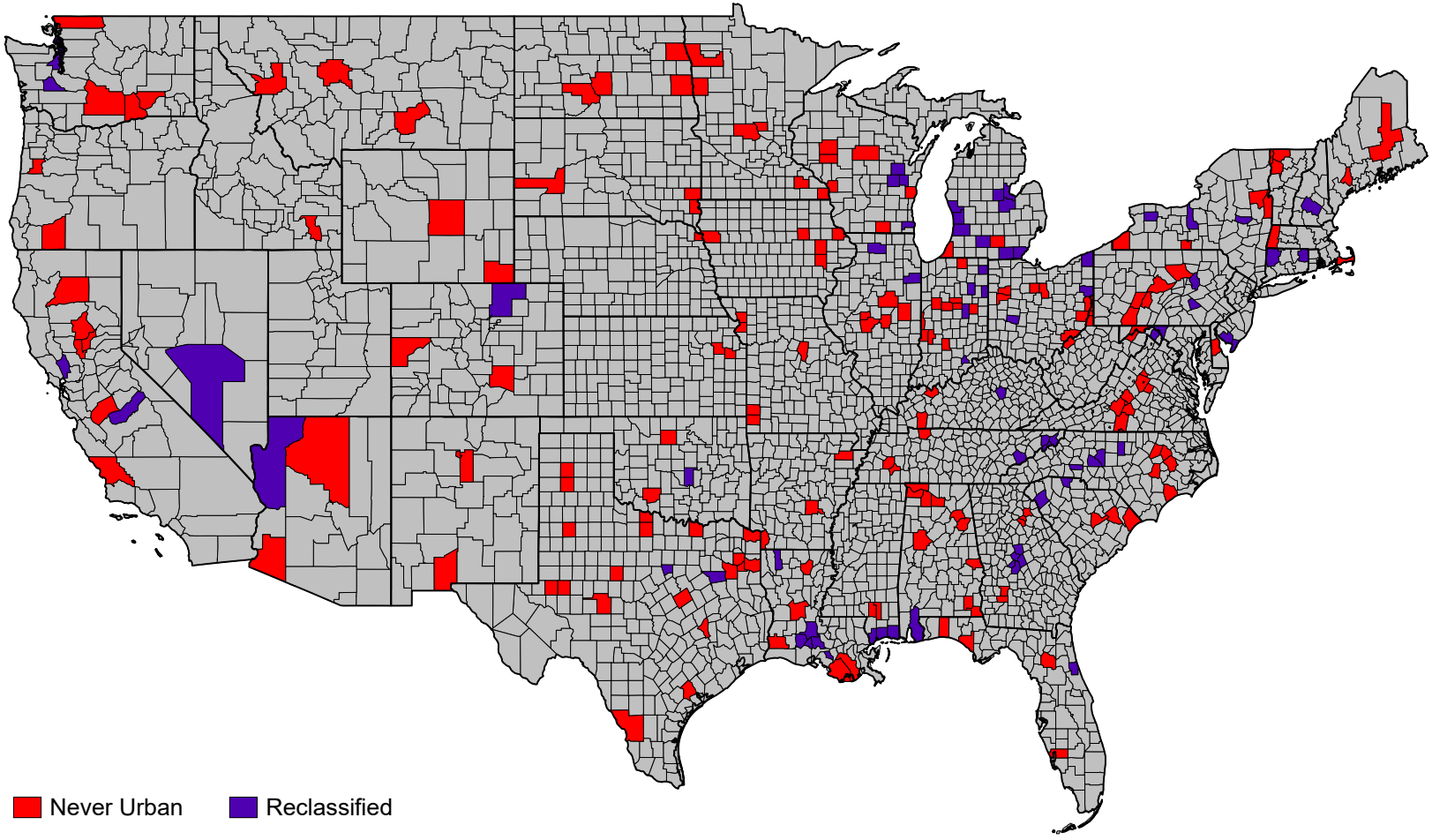
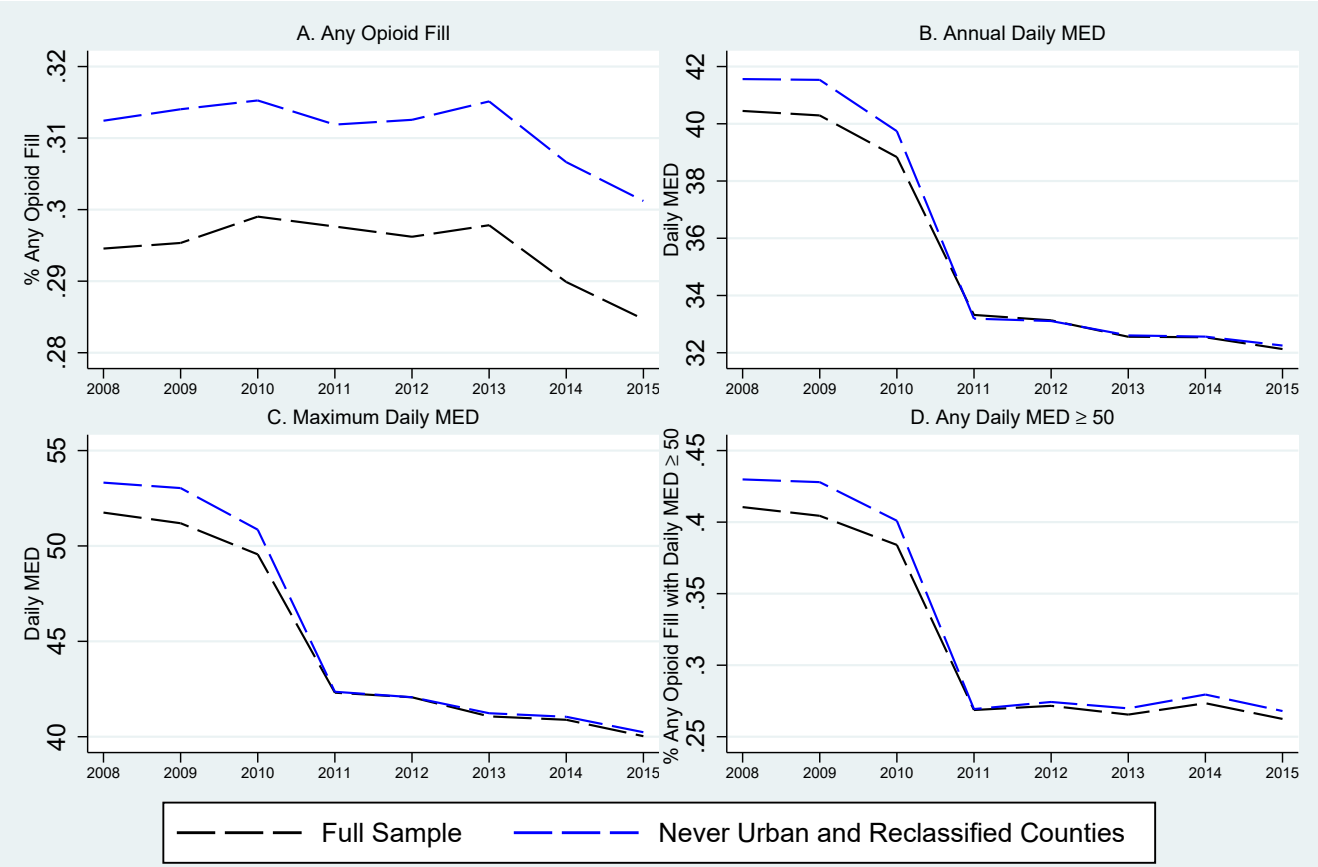
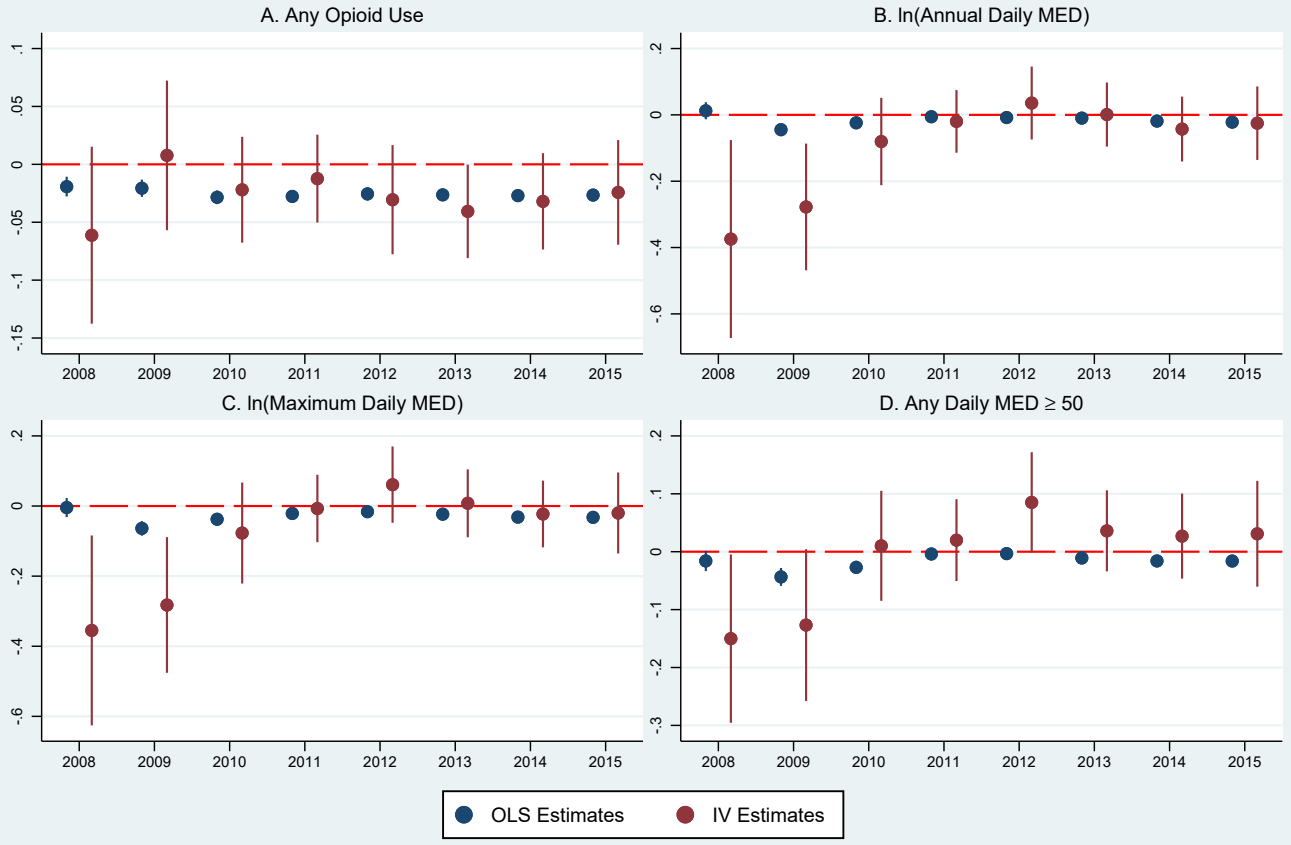


Figure 1.6: Measures of Opioid Use Over Sample Period



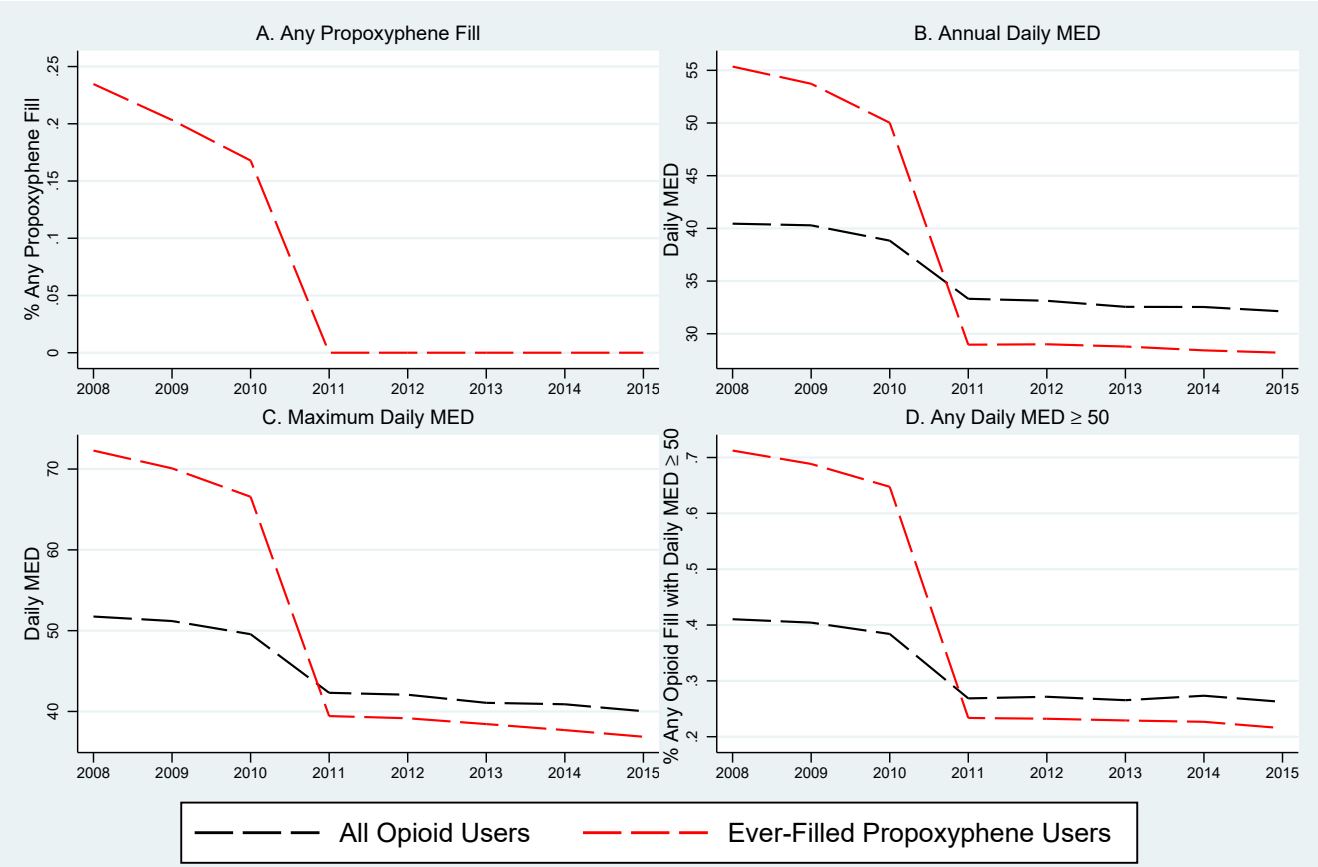
Note: Panels B.-D. are conditional on any opioid use.
Sources: Sources: 2008-2015 20 Percent Sample of Medicare Beneficiaries and Part D Event Files.

Figure 1.7: The Impact of MA-PDP Enrollment of Measures of Opioid Use Over Time



OLS estimates are estimates of β_1 from Equation 1.4 (and 95% CIs). IV estimates are estimates of β_1 from Equation 1.6 (and 95% CIs).
Standard errors are clustered at the county-level.
Sources: 2008-2015 20 Percent Sample of Medicare Beneficiaries and Part D Event Files.

Figure 1.8: Measures of Opioid Use Over Time by All Users and Ever-Filled Propoxyphene Users



Note: All panels are conditional on any opioid fill.
Sources: Sources: 2008-2015 20 Percent Sample of Medicare Beneficiaries and Part D Event Files.

Table 1.1: Statistical Area Classification Files and County Benchmark Payment Floors

Year	Classification File	Population Estimate	Lower Floor	Higher "Urban" Floor
1998	––	––	$367	––
1999	––	––	$379.84	––
2000	––	––	$401.61	––
2001 (Jan-Feb)	––	––	$415.01	––
2001 (Mar-Dec)	June 30, 1999	July 1, 1999	$475	$525
2002	June 30, 1999	July 1, 1999	$500.37	$553.04
2003	June 30, 1999	April 1, 2000	$495.39	$547.54
2004 (Jan-Feb)	June 30, 1999	April 1, 2000	$535.88	$592.29
2004 (Mar-Dec)	December 1, 2003	April 1, 2000	$555.42	$613.89

Notes: The table lists the statistical area and population files used to identify counties subject to payment floors, as well as the corresponding floor amounts. The June 30, 1999 classification file refers to the last file issued under the old metropolitan classification system. The December 1, 2003 file refers to the first file issued under the new metropolitan classification system.
Sources: Census Historical Delineation Files, Census Population Estimates, and CMS Ratebook Data.

Table 1.2: County Floor Status and the New Metropolitan Classification System

2001	2004	Counties	Name	2004 MSA Pop (1000s)	2000 Pop (1000s)	2010 Pop (1000s)	2004 FFS Rate
Non-Urban	Non-Urban	179	Never Urban	148.08	99.74	109.41	$539.51
				[44.89]	[54.32]	[62.30]	[$82.39]
Urban	Non-Urban	72	Reclassified	129.95	104.38	114.32	$564.56
				[65.34]	[56.48]	[62.99]	[$82.49]
−−	Non-Urban	784	−−	68.24	40.26	43.09	$525.91
				[46.99]	[28.19]	[32.31]	[$80.84]
Urban	Urban	582	−−	2,574.46	342.97	380.23	$597.71
				[3,733.96]	[614.28]	[651.34]	[$94.86]
Non-Urban	Urban	16	−−	324.04	109.95	121.08	$501.89
				[94.104]	[79.42]	[86.74]	[$58.18]
−−	Urban	146	−−	1,340.59	25.08	27.49	$539.75
				[1,470.49]	[16.79]	[18.69]	[$74.67]

Notes: Counties are grouped based on their status under the old (2001) and new (2004) metropolitan classification systems. Non-urban refers to counties that were part of MSAs with populations below 250,000 under the old classification system, or part of CBSAs with populations below 250,000 under the new classification system. Urban refers to counties that were part of MSAs with populations above 250,000 under the old classification system, or part of CBSAs with populations above 250,000 under the new classification system. 2004 FFS Rate refers to the average 2004 fee-for-service spending level used to determine county floor status. The table presents means and standard deviations (brackets).
Sources: Census Historical Delineation Files, Census Population Estimates, and CMS Ratebook Data.

Table 1.3: Examples of Never Urban and Reclassified Counties

		1999 MSA Classification			2003 CBSA Classification		
County	County Type	Name	Type	Pop	Name	Type	Pop
Auglaize, OH	Never Urban	Lima, OH	MSA	154,065	Wapakoneta, OH	Micro	46,230
Dale, AL	Never Urban	Dothan, AL	MSA	135,243	Enterprise-Ozark, AL	Micro	92,759
Ector, TX	Never Urban	Odessa-Midland, TX	MSA	242,238	Odessa, TX	Metro	121,124
Jones, GA	Reclassified	Macon, GA	MSA	321,586	Macon, GA	Metro	222,479
Kankakee, IL	Reclassified	Chicago-Gary-Kenosha, IL-IN-WI	CMSA*	8,885,919	Kankakee-Bradley, IL	Metro	103,825
Webster, LA	Reclassified	Shreveport-Bossier City, LA	MSA	377,673	Minden, LA	Micro	41,814

Notes: Under the old metropolitan classification system, MSA denotes Metropolitan Statistical Area and CMSA denotes Consolidated Metropolitan Statistical Area. Under the new metropolitan classification system, Metro denotes Metropolitan Statistical Area and Micro denotes Micropolitan Statistical Area.
*CMSAs were comprised of Primary Metropolitan Statistical Areas (PMSAs). Kankakee, IL was associated with the Kankakee, IL PMSA with a corresponding population of 102,720. However, benchmark floor amounts were assigned based on MSA or CMSA population.
Sources: Census Historical Delineation Files, Census Population Estimates, and CMS Ratebook Data.

Table 1.4: Summary Statistics Across the Cohort of Medicare Beneficiaries

	Full Sample	**Never Urban and Reclassified Counties**			
	All	All	Never Urban	Reclassified	Difference
	(1)	(2)	(3)	(4)	(5)
Individual Characteristics					
Age	74.82	74.69	74.78	74.52	-0.26
Female (%)	57.01%	56.62%	56.78%	56.26%	-0.52
White (%)	86.71%	92.26%	91.89%	93.09%	1.19
Black (%)	5.59%	3.58%	3.63%	3.46%	-0.17
Other Race (%)	7.69%	4.16%	4.47%	3.45%	-1.03
County Characteristics					
Population (1000s)	918.06	145.61	144.66	147.80	3.15
Disabled - All (%)	12.59%	13.91%	13.79%	14.16%	0.37
Disabled - Elderly (%)	36.28%	37.37%	37.64%	36.78%	-0.86
Poverty (%)	14.83%	16.03%	16.54%	14.87%	-1.67
Household Income ($1000s)	53.68	47.28	46.48	49.13	2.65
Unemployment Rate (%)	7.45%	7.40%	7.16%	7.96%	0.80
Land Area Per Capita	1.25	1.02	0.95	1.17	0.23
Physicians per 1000 people	0.75	0.72	0.77	0.61	-0.16
Hospitals per 1000 people	0.022	0.024	0.026	0.021	-0.005
Beds per 1000 people	3.08	3.73	4.09	2.89	-1.21
2004 Average FFS ($s)	604.89	554.89	550.45	565.01	14.56
In CBSA (%)	91.84%	100.00%	100.00%	100.00%	0.00
2003 CBSA Pop (1000s)	3,060.05	153.46	156.94	145.49	-11.44
State Characteristics					
PDMP - Any (%)	21.99%	22.15%	20.83%	25.17%	4.33
PDMP - Must Access (%)	9.82%	9.86%	9.65%	10.34%	0.69
Region of Residence					
Midwest (%)	23.15%	30.08%	29.34%	31.76%	2.42
Northeast (%)	18.17%	11.78%	10.86%	13.88%	3.02
South (%)	36.39%	39.57%	40.91%	36.53%	-4.38
West (%)	22.29%	18.57%	18.89%	17.83%	-1.06
Benchmark Amounts and Coverage					
Benchmark Amount ($s)	844.03	796.75	780.89	832.98	52.09
MA Enrollment (%)	31.57%	23.06%	19.97%	30.11%	10.14
MA-PDP Enrollment (%)	27.18%	17.23%	14.28%	23.97%	9.69
Part D Enrollment (%)	69.79%	64.99%	64.24%	66.71%	2.47
Counties	3,123	250	178	72	
Observations	35,404,744	3,464,563	2,409,236	1,055,327	

Note: Table contains sample means.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table 1.5: Summary Statistics for Medicare Beneficiaries with Part D Coverage

	Full Sample	**Never Urban and Reclassified Counties**			
	All	All	Never Urban	Reclassified	Difference
	(1)	(2)	(3)	(4)	(5)
Benchmark Amounts and Coverage					
Benchmark Amount ($s)	847.79	797.33	781.27	832.62	51.35
MA Enrollment (%)	43.15%	32.48%	28.12%	42.07%	13.96
MA-PDP Enrollment (%)	38.94%	26.51%	22.23%	35.94%	13.71
Part D Enrollment (%)	100.00%	100.00%	100.00%	100.00%	0
Measures of Opioid Use					
Any Opioid Fill (%)	29.36%	31.01%	31.10%	30.82%	-0.28
Conditional on Any Opioid Fill					
Annual Daily MED	34.71	34.93	35.09	34.58	-0.51
Max Daily MED	43.89	44.29	44.45	43.94	-0.51
Any Daily MED $\geq$ 50 (%)	30.55%	31.24%	31.43%	30.83%	-0.60
Counties	3,122	250	178	72	
Observations	24,709,626	2,251,773	1,547,762	704,011	

Note: Table contains sample means.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table 1.6: The Effect of Excess Payments to MA Plans on MA-PDP Enrollment

	MA-PDP Enrollment				
	(1)	(2)	(3)	(4)	(5)
All Beneficiaries					
Excess Payments	0.00263***	0.00253***	0.00253***	0.00266***	0.00265***
(N = 3,464,563)	(0.00051)	(0.00052)	(0.00052)	(0.00048)	(0.00047)
F-Statistic	27.04	33.03	27.25	20.02	21.65
Part D Beneficiaries					
Excess Payments	0.00362***	0.00358***	0.00357***	0.003617***	0.00362***
(N = 2,251,773)	(0.00059)	(0.00062)	(0.00062)	(0.000603)	(0.00059)
F-Statistic	36.39	33.15	42.97	32.29	34.63
Census Region and Year FEs		X	X	X	X
Individual Characteristics			X	X	X
County Characteristics				X	X
State Characteristics					X

Notes: Estimates corresponds to α_1 from Equation 1.5. Standard errors are clustered at the county-level. *** denotes significance at the one-percent level; ** denotes significance at the five-percent level; * denotes significance at the ten-percent level.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table 1.7: The Effect of Excess Payments to MA Plans on MA-PDP Enrollment, MA Enrollment, and Part D Coverage

	MA-PDP Enrollment (1)	**MA Enrollment** (2)	**Part D Enrollment** (3)
All Beneficiaries			
Excess Payments	0.00265***	0.00273***	0.00084***
(N = 3,464,563)	(0.00047)	(0.00046)	(0.00032)
Part D Beneficiaries			
Excess Payments	0.00362***	0.00349***	–
(N = 2,251,773)	(0.00059)	(0.00056)	

Notes: Estimates corresponds to α_1 from Equation 1.5. Standard errors are clustered at the county-level. *** denotes significance at the one-percent level; ** denotes significance at the five-percent level; * denotes significance at the ten-percent level.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table 1.8: The Impact of MA-PDP Enrollment on Any Opioid Use

	Any Opioid Use			
	Mean	OLS Estimate	IV Estimate	Exog (p-value)
	(1)	(2)	(3)	(4)
Part D	0.3101	-0.0258***	-0.0262	0.9813
(N = 2,251,773)		(0.0018)	(0.0201)	
Part D: Chronic Conditions	0.3367	-0.0205***	-0.014	0.7611
(N = 1,485,171)		(0.0019)	(0.023)	
All Beneficiaries	0.2016	0.0993***	0.084***	0.6259
(N = 3,464,563)		(0.0034)	(0.032)	

Notes: Column 1 contains outcome averages. Column 2 contains OLS estimates of β_1 from Equation 1.4. Column 3 contains 2SLS estimates of β_1 from Equation 1.6. Column 4 contains p-values from a robust test of exogeneity (Wooldridge 1995). Standard errors are clustered at the county-level. *** denotes significance at the one-percent level; ** denotes significance at the five-percent level; * denotes significance at the ten-percent level.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table 1.9: The Impact of MA-PDP Enrollment on Intensity of Opioid Use

	ln(Annual Daily MED)				**ln(Max Daily MED)**				**Any Daily MED $\geq$ 50**			
	Mean[a] (1)	OLS Estimate (2)	IV Estimate (3)	Exog (p-value) (4)	Mean[a] (5)	OLS Estimate (6)	IV Estimate (7)	Exog (p-value) (8)	Mean (9)	OLS Estimate (10)	IV Estimate (11)	Exog (p-value) (12)
All Part D	34.93	-0.0157***	-0.060	0.3389	44.29	-0.0289***	-0.049	0.6490	0.3124	-0.0154***	0.010	0.4439
(N = 698,382)		(0.0046)	(0.049)			(0.0049)	(0.048)			(0.0034)	(0.035)	
Chronic Conditions	34.41	-0.0159***	-0.0568	0.3947	43.78	-0.0285***	-0.048	0.6889	0.3071	-0.0152***	0.010	0.4540
(N = 499,989)		(0.0047)	(0.0505)			(0.0051)	(0.049)			(0.0035)	(0.036)	

Notes: Columns 1, 5, and 9 contain outcome averages. Columns 2, 6, and 10 contain OLS estimates of β_1 from Equation 1.4. Columns 3, 7, and 11 contain 2SLS estimates of β_1 from Equation 1.6. Columns 4, 8, and 12 contain p-values from a robust test of exogeneity (Wooldridge 1995). Standard errors are clustered at the county-level. *** denotes significance at the one-percent level; ** denotes significance at the five-percent level; * denotes significance at the ten-percent level.
[a]Averages are not log transformed.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table 1.10: The Impact of MA-PDP Enrollment on Propoxyphene Use and Intensity of Opioid Use (2008 and 2009)

	Mean (1)	OLS Estimate (2)	IV Estimate (3)	Exog (p-value) (4)
A. Any Propoxyphene Use				
All Opioid Users	0.2478	-0.031***	-0.189**	0.0280
(N = 123,503)		(0.0087)	(0.079)	
Non-Propoxy Users	0	–	–	–
(N = 92,899)				
B. Any Daily MED $\geq$ 50				
All Opioid Users	0.4289	-0.0319***	-0.139**	0.0864
(N = 123,503)		(0.0075)	(0.062)	
Non-Propoxy Users	0.2953	-0.0178**	-0.018	0.9985
(N = 92,899)		(0.0076)	(0.062)	

Notes: Columns 1 contains outcome averages. Column 2 contains OLS estimates of β_1 from Equation 1.4. Column 3 contains 2SLS estimates of β_1 from Equation 1.6. Column 4 contains p-values from a robust test of exogeneity (Wooldridge 1995). Standard errors are clustered at the county-level. *** denotes significance at the one-percent level; ** denotes significance at the five-percent level; * denotes significance at the ten-percent level.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

CHAPTER II

Insurer Incentives and Benefit Design for Opioids

2.1 Introduction

In 2018, over 67 thousand Americans died from a drug overdose (Hedegaard et al., 2020). Although the substantial rise in drug-related mortalities over the past decade has been largely driven by illicit opioid use, the origins of this epidemic are rooted in opioid prescribing patterns that began in the 1990s and persisted throughout the 2000s. While pharmaceutical companies, physicians, and patients have received increased scrutiny in recent years over their respective roles in the ongoing crisis, the actions and behaviors of private health insurers have gone largely overlooked. These firms play an integral role in coordinating care between large segments of the U.S. population and health care providers; as a result, health insurers are uniquely positioned to monitor and observe patterns of opioid prescribing and use. Furthermore, despite recent efforts at the federal level to address the opioid epidemic, many public health advocates contend that the most impactful change will occur through communal ventures. Because of their influence in local health care markets, developing a better understanding of how private health insurers' incentives interact with enrollee opioid use is of first order concern.

In this study, I examine how the breadth of coverage that private health insurers provide interacts with benefit design for prescription opioids. I study this issue within

the context of the Medicare Part D program, which features two types of private health insurance plans: stand-alone Part D Plans (SA-PDPs) and Medicare Advantage Part D Plans (MA-PDPs). While SA-PDPs provide coverage for prescription drugs only, MA-PDPs provide coverage for both drug and non-drug medical expenditures. Because of the breadth of coverage that they provide, MA-PDPs have an incentive to consider how enrollees' opioid use interacts with other modes of treatment, such as hospital care. SA-PDPs face no such incentive. I examine whether these differences in incentives manifest through differences in benefit design for opioids.

To conduct my analysis, I leverage evidence on the link between opioid use and adverse health events that can lead to hospitalizations. While prescription opioids have a negative connotation surrounding them, these drugs continue to serve as a primary form of treatment for both chronic and acute pain. This issue is particularly salient in the context of the Medicare Part D program; the elderly face higher rates of chronic pain stemming from conditions that become more common later in life, such as arthritis. To distinguish between therapeutic and hazardous opioid use, I exploit evidence from the medical literature on the link between high daily dosages of opioids and hospitalizations. A large body of literature finds that high daily dosages of opioids can lead to a range of adverse health events, including unintentional overdose, fractures and falls from the side-effects of these drugs, and, in extreme cases, mortality (Dunn et al., 2010; Saunders et al., 2010; Bohnert et al., 2011). Because benefit design directly impacts enrollee drug use, I hypothesize that MA-PDPs structure benefits in a way that limits enrollee use of high dosage opioids. To examine this issue, I test for differences in benefit design for opioids across MA-PDPs and SA-PDPs.

I use Part D benefit design data that spans various years throughout 2008 and 2015 to examine my research question. I focus on benefit design outcomes that are based on utilization management rules; these include prior authorization requirements and quantity limit restrictions. I find evidence that MA-PDPs design benefits to limit high dosage opi-

oid use; relative to opioids covered by SA-PDPs, opioids covered by MA-PDPs are more likely to have a quantity limit restriction. Conditional on a quantity limit restriction, opioids covered by MA-PDPs have lower daily dosage allowances relative to opioids covered by SA-PDPs. These effects are primarily driven by differences in benefit design from early in the sample period, when utilization management rules were less frequently imposed. In addition, I find that MA-PDPs were less likely to provide coverage for propoxyphene, a high dosage opioid that was withdrawn from the market in 2010.

This study adds to two strands of literature. The first examines the effect of enrollment in an MA-PDP on opioid use (Baker et al., 2020; Rhodes, 2020). Although these studies find that enrollment in an MA-PDP lowers measures of opioid use, they do not provide direct evidence on how this occurs. My results suggest that at least part of this effect is driven by benefit design mechanisms.

The second strand of literature examines whether MA-PDPs internalize externalities from prescription drugs. Previous studies show that MA-PDPs internalize positive externalities from prescription drugs, as evidenced by the finding that, relative to SA-PDPs, MA-PDPs set lower cost-sharing requirements for drugs that reduce hospitalizations (Lavetti and Simon, 2018; Starc and Town, 2019). By showing that MA-PDPs set more restrictive utilization management rules for opioids, a class of drugs that has been associated with increased hospitalizations, I provide evidence that MA-PDPs internalize negative externalities from prescription drugs.

2.2 Background

The Medicare Part D program was first introduced through the Medicare Modernization Act of 2003, and, beginning in 2006, Medicare beneficiaries were given the option to enroll in a highly subsidized drug plan. The Part D program is administered by two types of private health insurance plans: Medicare Advantage Part D Plans (MA-PDPs),

which are integrated into parent Medicare Advantage plans, and Stand-Alone Part D plans (SA-PDPs), which generally supplement enrollment into traditional fee-for-service Medicare. While MA-PDPs operate at the county-level, SA-PDPs operate at a regional-level, with 34 regions altogether. In exchange for providing coverage, both MA-PDPs and SA-PDPs receive a monthly, risk-adjusted payment for each enrolled beneficiary. The risk-adjustment formula factors in beneficiary diagnoses from the previous year, and the payment is expected to cover the costs of enrollee drug expenditures.

Part D benefit design is characterized by two factors: coverage and cost-sharing requirements (Figure 2.1). Part D plans begin by selecting a plan formulary, which constitutes a list of covered drugs. Beneficiaries pay 100 percent of the costs of drugs that do not appear on a plan formulary, while plans pay for all but the out-of-pockets costs for drugs that do appear on this list. Part D formularies must abide by two regulations: first, they must cover all drugs in six therapeutic classes (including anticancer drugs and antiretroviral drugs). Second, Part D formularies must cover at least two drugs in each U.S. Pharmacopeia therapeutic class, a drug classification system developed in response to the Part D program. Opioids have consistently appeared on this list, meaning that Part D plans have been required to provide coverage for at least two opioids since the program's introduction in 2006.

In addition to outlining the list of covered drugs, the plan formulary also lists utilization management rules and the level of cost-sharing associated with each drug. Utilization management rules are controls that Part D plans can impose on individual drugs to limit the amount of medication that a beneficiary receives at a given time. These include prior authorization requirements, quantity limit restrictions, and step therapy requirements. Prior authorization requires that prescribers contact the Part D plan prior to issuing a prescription. A quantity limit restriction sets a cap on the number of prescriptions that the plan will cover within a given timeframe. Step therapy requires that beneficiaries try a more cost-effective form of treatment (i.e. generic drug) before they can purchase a

more expensive treatment (i.e. branded drug).

While Part D plans have only one formulary, the same formulary often corresponds to multiple Part D plans. Cost-sharing requirements are determined at both the formulary-level and the plan-level. Part D formularies are partitioned into tiers, and all drugs that appear on the same tier have the same co-pay or coinsurance amount. Typically, Part D formularies are stratified into four tiers, with lower tiers corresponding to lower cost-sharing amounts and higher tiers corresponding to higher cost-sharing amounts. Part D plans that share the same formulary have the same list of covered drugs and drug tier placement; however, plans are given broad latitude in assigning levels of cost-sharing across drug tiers. For example, while one plan might assign a five-dollar cost-sharing requirement for all tier one drugs, another plan with the same formulary might assign an eight-dollar requirement for the same set of (tier one) drugs. However, plans are required to meet the minimum actuarial coverage mandated by the Part D "standard benefit," a complex, nonlinear benefit design. While the details of this pricing structure are beyond the scope of this paper, it is worth noting that this requirement prevents plans from setting overly generous or restrictive coverage for a large fraction of covered drugs.

2.2.1 Strategic Benefit Design in the Part D Program

The market-based design of the Part D program was intended to reward lower-cost plans with greater market shares. However, a growing body of literature finds that Part D plans attempt to increase profit margins through strategic benefit design. This occurs along two dimensions – advantageous selection of profitable enrollees and internalizing externalities from prescription drugs. The findings from both strands of literature offer important implications for my empirical approach.

Two recent studies find that Part D plans exploit inaccuracies in Medicare risk-adjustment models to advantageously select enrollees (Carey, 2017; Lavetti and Simon, 2018). The Medicare program uses risk-adjustment models to calculate the per-enrollee

payments that private health insurers receive from the federal government in exchange for providing either MA or Part D coverage (or both). These models assign individualized risk scores to Medicare beneficiaries, with higher risk scores corresponding to higher payments. The Part D risk-adjustment model assigns higher risk scores to beneficiaries diagnosed with conditions that are associated with high drug expenditures, while the MA risk-adjustment model assigns higher risk scores to beneficiaries diagnosed with conditions that are associated with high physician and hospital expenditures. Individualizing payments via risk-adjustment models is intended to make insurers indifferent between enrolling healthy and sick beneficiaries. However, inaccuracies in these models can motivate plans to select along other dimensions.

When the Part D risk-adjustment model is not updated frequently, the entry of new drugs and competitors generates inaccuracies in risk-adjusted payments. Because branded drugs are not supplied competitively, diagnoses exposed to generic competition became more profitable, while diagnoses exposed to new drug entry became less profitable. Carey (2017) shows that SA-PDPs exploit new drug entry to advantageously select enrollees. The study finds that SA-PDPs set lower out-of-pocket costs for drugs used in the treatment of conditions made profitable by generic entry, while these plans set higher out-of-pocket costs for drugs used in the treatment of conditions made unprofitable by brand entry.

MA-PDPs have an incentive to attract enrollees with conditions made profitable due to inaccuracies in the MA risk-adjustment model (McWilliams et al., 2012; Newhouse et al., 2013; Brown et al., 2014). Lavetti and Simon (2018) show that, relative to SA-PDPs, MA-PDPs offer more generous coverage for drugs taken by patients who are diagnosed with conditions made profitable due to these inaccuracies. For example, the study finds that MA-PDPs generally profit from enrolling beneficiaries with acute leukemia; flaws in the MA risk-adjustment calculator make the costs of treatment associated with this condition generally lower than the corresponding risk-adjusted payments. Because an acute

leukemia diagnosis is predictive of fentanyl use, Lavetti and Simon (2018) hypothesize that MA-PDPs offer more generous coverage for fentanyl products to attract enrollees with this condition. In line with this hypothesis, they find that MA-PDP enrollees pay 80 percent less in out-of-pocket costs for fentanyl drugs relative to SA-PDP enrollees.

Because of the breadth of coverage that they provide, MA-PDPs also have a financial incentive to consider the complementarity or substitutability between drug and non-drug medical treatments when designing Part D benefits. Two recent studies examine whether MA-PDPs harness benefit design to internalize positive externalities from prescription drugs (Lavetti and Simon, 2018; Starc and Town, 2019). The empirical approach in these studies is motivated by two previous findings; first, that consumers are price-sensitive in their demand for drugs, and second, that drug treatments are effective in keeping individuals with chronic conditions out of the hospital. In light of these findings, both studies hypothesize that MA-PDPs offer more generous coverage for drugs that treat chronic conditions relative to SA-PDPs. Lavetti and Simon (2018) find that out-of-pocket costs for drugs used in the treatment of chronic conditions are six to eight percent lower in MA-PDPs relative to SA-PDPs. Similarly, Starc and Town (2019) find that enrollment in an MA-PDP increases beneficiary drug expenditures, with effects concentrated among drugs used in the treatment of chronic conditions.

2.2.2 Efforts to Manage Opioid Use through Benefit Design

Several recent studies evaluate efforts by both public and private health insurers to manage enrollee opioid use through benefit design. Morden et al. (2008) examine the impact of state Medicaid prior authorization requirements on the use of extended release oxycodone (OxyContin). They find that states with stricter requirements exhibited slower growth in the use of these drugs. García et al. (2016) evaluate the effect of a 2012 initiative by Blue Cross Blue Shield of Massachusetts that introduced prior authorization requirements on new prescriptions for short-acting opioids and all extended release opioid

prescriptions. They find that 21 million fewer opioid doses were administered in the three years following the implementation of this requirement. Barnett et al. (2018) evaluate a 2015 initiative by Blue Cross of California that introduced a strict prior authorization requirement on extended release oxycodone. While they find that the initiative led to a substantial reduction in the use of extended release oxycodone, this decline was offset by an increase in the use of short acting oxycodone, resulting in no overall change in levels of opioid use.

2.3 Data and Methods

I use Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files from the Centers for Medicare and Medicaid Services to test for differences in benefit design for opioids across MA-PDPs and SA-PDPs. These data contain detailed information on the universe of Part D formularies and plans, including the list of covered drugs on each formulary, utilization management rules corresponding to each formulary-drug combination, and the level of cost-sharing associated with each plan-drug combination. For formulary-drug combinations that have a quantity limit restriction, the data contain both the quantity limit amount and the days limit; for example, 90 tablets within 30 days. I use data from 2008, 2009, 2011, 2013, and 2015. These data years represent a period of significant change in the medical community's perception of safe opioid prescribing levels; between 2009 and 2011, researchers documented a heightened risk of adverse health events linked to high daily dosages of opioids, particularly among the elderly (Dunn et al., 2010; Saunders et al., 2010; Bohnert et al., 2011).

I test for differences in utilization management rules across MA-PDPs and SA-PDPs to determine whether MA-PDPs internalize negative externalities from opioids. I focus on utilization management outcomes (rather than cost-sharing requirements), for two reasons; first, my empirical approach is motivated by evidence from the medical literature

on the link between high daily dosages of opioids and adverse health events. Utilization management rules, including prior authorization requirements and quantity limit restrictions, can be used by Part D plans to both limit and manage daily dosages of opioids. Conversely, cost-sharing requirements within the Part D program cannot be structured around daily dosage levels.

Second, it is unclear what information can be gleaned from differences in cost-sharing requirements for opioids. While higher cost-sharing requirements may be indicative of plans' efforts to limit enrollees' opioid use more generally, this finding may also capture other unknown factors. For example, Lavetti and Simon (2018) find that MA-PDPs set lower cost-sharing requirements for fentanyl drugs to attract more profitable enrollees. There is no evidence that inaccuracies in risk-adjustment models, or other potential confounders, are reflected in utilization management outcomes.

I construct four outcomes related to utilization management rules. First, I construct an indicator for whether a formulary-drug combination corresponds with any utilization management rule, which I define as either a prior authorization requirement or a quantity limit restriction.[1] Next, I construct separate indicators for prior authorization requirements and quantity limit restrictions. Finally, I calculate the maximum daily morphine equivalent dosage (MED) allowed under each quantity limit restriction. This field is constructed as follows: first, I identify the total morphine milligram equivalency corresponding to the quantity limit restriction. This is calculated by multiplying the allowed quantity amount by the drug strength and an ingredient specific conversion factor (Table A.2). I then divide this figure by the corresponding days supply restriction. For example, a quantity limit restriction of 90 tablets within 30 days for 10 milligrams of oxycodone has a maximum daily MED allowance of 45 ((90*10*1.5)/30).

[1] I omit step therapy requirements from this analysis. Step therapy requirements are rarely used, and there is no evidence that this requirement would be effective in managing enrollees' use of opioids.

2.3.1 Empirical Strategy

Because utilization management rules are determined at the formulary-level (rather than the plan-level), I test for differences in benefit design for opioids at the formulary-drug-level. I stratify Part D formularies into three categories. The first category is comprised of formularies that are used exclusively by SA-PDPs ("SA-PDP Only"); the second category is comprised of formularies that are used by both types of plans ("SA-PDP and MA-PDP"); and, the third category is comprised of formularies that are used exclusively by MA-PDPs ("MA-PDP Only"). Figure 2.2 provides an example of each type of formulary from data year 2008. Formulary "00008371" is an example of an SA-PDP Only formulary; this formulary is used by only one plan, "WellCare Classic", an SA-PDP. Formulary "00008307" is an example of an SA-PDP and MA-PDP formulary; this formulary is used by both an SA-PDP ("BlueShield Medicare Rx Enhanced Plan") and an MA-PDP ("BlueShield 65 Plus"). Finally, formulary "00008308" is an example of an MA-PDP Only formulary; this formulary is used exclusively by "BlueShield 65 Plus Choice Plan (Partial)", an MA-PDP.

The number of formularies generally increases throughout the sample period, going from 211 in 2008 to 240 in 2015 (Figure 2.3). While the number of SA-PDP Only formularies does not change substantially, the number of enrollees in SA-PDPs that use these formularies doubles, going from nine million in 2008 to 18 million in 2015 (Figure 2.4). The number of SA-PDP and MA-PDP formularies is halved throughout the data years, declining from 41 in 2008 to 20 in 2015; this corresponds with a substantial reduction in the number of Medicare beneficiaries enrolled in Part D plans that use these formularies. Conversely, the number of MA-PDP Only formularies generally increases throughout the data years, going from 123 in 2008 to 176 in 2015. The increase in the number of MA-PDP Only formularies corresponds with a significant rise in the number of enrollees in MA-PDPs that use these formularies, increasing from three million in 2008 to 11 million

in 2015.

Table 2.1 contains summary statistics for the sample of formularies used by Part D plans. There are many more MA-PDP Only formularies (728) than there are SA-PDP Only formularies (235) and SA-PDP and MA-PDP formularies (142). While the average SA-PDP Only formulary is used by 19 SA-PDPs, the average MA-PDP Only formulary is used by only seven MA-PDPs. The average SA-PDP and MA-PDP formulary is used by 27 Part D plans; roughly 13 of these plans are SA-PDPs, while 15 of these plans are MA-PDPs. SA-PDP Only formularies have, on average, the largest number of Medicare enrollees at over 260 thousand. MA-PDP Only formularies have, on average, the smallest number of Medicare enrollees at 42 thousand. Given that SA-PDPs operate at a regional-level (comprised of individual states or groups of states), while MA-PDPs operate at the county-level, the differences in average enrollment levels across formulary types is expected.

The average formulary contains 3,705 unique drug products (National Drug Codes), of which 154 are opioids. However, there are significant differences in the average number of covered drugs (and opioids) across formulary types. Formularies that correspond to both SA-PDPs and MA-PDPs contain, on average, the highest number of covered drugs at four thousand, with 178 opioids. MA-PDP Only formularies contain, on average, close to 3.7 thousand drugs, while SA-PDP Only formularies list only 3.6 thousand drugs. The smaller number of covered drugs listed on both SA-PDP Only formularies and MA-PDP Only formularies corresponds with a smaller number of covered opioids (150). All formularies contain at least one opioid, in line with U.S. Pharmacopeia Guidelines.

To determine whether benefit design for prescription opioids differs across MA-PDPs and SA-PDPs, I compare utilization management rules for opioids across the three different types of formularies. I hypothesize that, relative to opioids listed on formularies used exclusively by SA-PDPs (SA-PDP Only), opioids listed on formularies used exclusively by MA-PDPs (MA-PDP Only) are more likely to have a corresponding utilization

management rule. This hypothesis emerges from the differences in coverage requirements across MA-PDPs and SA-PDPs; MA-PDPs have an incentive to limit high dosage opioid use, while SA-PDPs do not. Similarly, because SA-PDP and MA-PDP formularies are used by MA-PDPs, I hypothesize that opioids listed on these formularies will also be more likely to have a corresponding utilization management rule relative to opioids listed on formularies used exclusively by SA-PDPs. However, as evidenced in Figures 2.3 and 2.4, these formularies become much less prevalent later in the sample period, suggesting that both MA-PDPs and SA-PDPs may find it more strategic to use formularies that are tailored to their coverage.

Table 2.2 presents summary statistics at the formulary-drug-level. Column 1 presents sample means for drugs listed on all Part D formularies; column 2 presents sample means for drugs listed on formularies that are used exclusively by SA-PDPs; column 3 presents sample means for drugs listed on formularies that are used by SA-PDPs and MA-PDPs; and, column 4 presents sample means for drugs listed on formularies that are used exclusively by MA-PDPs. In columns 4 and 6, I present difference-in-means between drugs listed on SA-PDP and MA-PDP formularies (column 4) and drugs listed on MA-PDP Only formularies (column 6) relative to drugs listed on SA-PDP Only formularies.

In panel A of Table 2.2, I present summary statistics for all formulary-drug combinations. Roughly one-quarter of drugs have any utilization management rule. SA-PDP Only formularies have the highest percentage of drugs with any utilization management rule, at 26.8 percent. These formularies also have the highest percentage of drugs with a quantity limit restriction (15.4 percent). SA-PDP and MA-PDP formularies have the lowest percentage of drugs with a corresponding utilization management rule (24.5 percent), and only 12.5 percent of drugs that appear on these formularies have a prior authorization requirement. MA-PDP Only formularies have the lowest percentage of drugs with a quantity limit restriction, at 13.8 percent.

In panel B of Table 2.2, I present summary statistics for all formulary-opioid combina-

tions. Relative to all covered drugs, opioids are much more likely to have a corresponding utilization management rule (46.3 percent versus 25.6 percent). This is primarily driven by higher percentages of quantity limit restrictions (41.8 percent); conversely, the percentage of opioids with a prior authorization requirement is slightly lower than the percentage of all drugs with this requirement (11.4 percent versus 14.1 percent). MA-PDP Only formularies have the highest percentage of opioids with a quantity limit restriction (42.9 percent); this figure is over three percentage points higher than the percentage of opioids listed on SA-PDP Only formularies with a quantity limit restriction (39.2 percent). At 167 milligrams per day, MA-PDP Only formularies have the lowest average maximum daily MED allowance; this figure is roughly ten milligrams lower than the average allowance corresponding to opioids listed on SA-PDP Only formularies with a quantity limit restriction, and seven milligrams lower than opioids listed on SA-PDP and MA-PDP formularies with a quantity limit restriction.

2.3.2 Econometric Methods

The summary statistics presented in Table 2.2 suggest that MA-PDPs harness benefit design to manage enrollees' opioid use. While drugs listed on formularies used by MA-PDPs are generally less likely to have a corresponding utilization management rule relative to drugs listed on formularies used exclusively by SA-PDPs, opioids listed on formularies used by MA-PDPs are generally more likely to have a utilization management rule relative to opioids listed on formularies used exclusively by SA-PDPs. However, these differences may capture factors that are unrelated to efforts by MA-PDPs to manage daily dosage levels through benefit design. For example, these differences may reflect coverage for different drugs. If MA-PDPs are more likely to cover fentanyl drugs relative to SA-PDPs (and fentanyl drugs are more likely to correspond with a utilization management rule), then this would discredit the interpretation that MA-PDPs harness benefit design to manage enrollees' opioid use. To probe this issue, I estimate the following specification

on the sample of formulary-opioid combinations:

$$Y_{d_{(i)}ft} = \beta_0 + \beta_1 SAandMA_f + \beta_2 MAOnly_f + \gamma_t + [(\gamma_t \times \tau_i) + (\gamma_t \times \alpha_d)] + \epsilon_{d_{(i)}ft} \quad (2.1)$$

$Y_{d_{(i)}ft}$ represents utilization management outcome for opioid drug d (with primary ingredient i) listed on formulary f in year t. $SAandMA_f$ is an indicator for whether the opioid drug corresponds with an SA-PDP and MA-PDP formulary and $MAOnly_f$ is an indicator for whether the opioid drug corresponds with an MA-PDP Only formulary. The omitted formulary category is that corresponding to formularies that are used exclusively by SA-PDPs (SA-PDP Only). Equation 2.1 contains year fixed effects (γ_t) to control for benefit design shocks that are common across all formularies with a given year. $\epsilon_{d_{(i)}ft}$ is an error term that allows for arbitrary correlation within formularies.

β_1 and β_2 are the coefficients of interest in Equation 2.1. Estimates of β_1 and β_2 capture the average differences in benefit design outcomes for opioids covered on SA-PDP and MA-PDP formularies (β_1) and opioids covered on MA-PDP Only formularies (β_2), relative to opioids covered on formularies that are used exclusively by SA-PDPs. Because MA-PDPs have an incentive to consider the link between enrollee opioid use and adverse health events (and SA-PDPs do not face this incentive), I hypothesize that $\beta_1 > 0$ and $\beta_2 > 0$ for binary utilization management outcomes. Positive estimates of β_1 and β_2 would imply that opioids listed on formularies used by MA-PDPs have more restrictive benefit design requirements relative to opioids listed on formularies used exclusively by SA-PDPs. For the continuous maximum daily MED allowance outcome, I hypothesize that $\beta_1 < 0$ and $\beta_2 < 0$; a negative estimate would indicate that formularies used by MA-PDPs have a lower maximum daily dosage allowance relative to formularies used exclusively by SA-PDPs. I estimate the logarithmic transformation of maximum daily MED allowance; a Box-Cox test strongly favors the log specification, with a parameter estimate of 0.0001.

In addition to baseline estimates of Equation 2.1, I also present estimates from models that include year by ingredient effects ($\gamma_t \times \tau_i$) and year by drug effects ($\gamma_t \times \alpha_d$). I compare estimates of β_1 and β_2 from models that include these additional controls to probe whether differences in benefit exist within coverage for the same year-ingredient combinations (i.e. oxycodone in 2009) and coverage for the same year-drug combinations (i.e. OxyContin 20 milligrams in 2009). I estimate all models via ordinary least squares (OLS).

2.4 Results

Table 2.3 contains estimates of β_1 and β_2 from Equation 2.1. Columns 1 through 3 present estimates from models in which the outcome is any utilization management rule; columns 4 through 6 present estimates from models in which the outcome is a prior authorization requirement; columns 7 through 9 present estimates from models in which the outcome is a quantity limit restriction; and, columns 10 through 12 present estimates from models in which the outcome is the logarithmic transformation of the maximum daily MED allowance, conditional on a quantity limit restriction. Within each outcome, I present estimates from the baseline model, as well as estimates from models that include year by ingredient effects and year by drug effects.

Relative to opioids listed on formularies used exclusively by SA-PDPs, opioids listed on SA-PDP and MA-PDP formularies are more likely to have a corresponding utilization management rule. The estimate of 0.06 represents a 13 percent increase from the overall percentage of opioids with any utilization management rule (46.3 percent). The inclusion of both year by ingredient effects and year by drug effects has minimal impact on either the magnitude or the precision of estimates of β_1, indicating that differences in utilization management rules persist within coverage for the same ingredients and drugs within the same year. Opioids listed on MA-PDP Only formularies are, on average, less likely to have

a corresponding utilization management rule relative to opioids listed on SA-PDP Only formularies. However, the estimate of -0.02 is small in magnitude, representing only a 3.5 percent decline from the overall mean, and imprecise. The inclusion of year by ingredient effects and year by drug effects again has minimal impact on either the magnitude or the precision of these estimates.

The increased likelihood of a utilization management rule among opioids listed on SA-PDP and MA-PDP formularies is driven by higher rates of quantity limit restrictions. Relative to opioids listed on formularies used exclusively by SA-PDPs, opioids listed on SA-PDP and MA-PDP formularies are, on average, seven percentage points more likely to have a corresponding quantity limit restriction. This represents a 17 percent increase from the overall mean of 42 percent. This estimate is significant at the one-percent level, and insensitive to the inclusion of year by ingredient effects and year by drug effects. Conversely, there is no statistical difference in the likelihood of a prior authorization requirement across opioids listed on SA-PDP Only formularies and opioids listed on SA-PDP and MA-PDP formularies; while the estimate of 0.01 constitutes a ten percent increase from the overall mean of 11 percent, this estimate is noisy and I am unable to rule out large effects in either direction.

Relative to opioids listed on SA-PDP Only formularies, opioids listed on MA-PDP Only formularies are less likely to have either a prior authorization requirement or a quantity limit restriction. Estimates of β_2 corresponding to both of these outcomes indicate a one percentage point reduction; this ranges from a three percent reduction from the overall quantity limit restriction rate (42 percent), to an 11 percent reduction from the overall prior authorization requirement (11 percent). However, all estimates are noisy, and I am unable to rule out large effects in either direction when the outcome is a prior authorization requirement.

Although opioids listed on MA-PDP Only formularies are less likely to have a quantity limit restriction than opioids listed on formularies used exclusively by SA-PDPs,

conditional on having a quantity limit restriction, opioids listed on these formularies have substantially lower maximum daily MED allowances. The estimate of -0.06 implies that, on average, the maximum daily MED allowance is six percent lower among opioids listed on MA-PDP Only formularies relative to opioids listed on SA-PDP Only formularies. This estimate is significant at the one-percent level. Although the inclusion of year by ingredient effects and year by drug effects reduces the magnitude of the estimate, these estimates continue to indicate a statistically significant difference.

Conditional on a quantity limit restriction, opioids listed on SA-PDP and MA-PDP formularies have, on average, a six percent lower maximum daily MED allowance relative to opioids listed on SA-PDP Only formularies. While this estimate is significant at the five-percent level, the inclusion of year by ingredient effects and year by drug effects reduces both the magnitude and the precision of this estimate. These results suggest that the differences in daily MED allowances across these two types of formularies are driven by differences in MED allowances for opioids that are specific to formulary types, rather than opioids that are common across both formulary types.

2.5 Sensitivity Analyses

2.5.1 Utilization Management Rules for Other Drugs

The results indicate that opioids listed on formularies used by MA-PDPs are more likely to correspond with a utilization management rule relative to opioids listed on formularies used exclusively by SA-PDPs. While this finding may be indicative of efforts by MA-PDPs to limit or manage enrollees' use of opioids, it may also reflect the fact that MA-PDPs use formularies with higher rates of utilization management rules across all covered drugs, not just opioids. As a result, the findings may capture restrictive benefit design more broadly, as opposed to utilization management rules tailored specifically towards opioids.

To determine whether formularies used by MA-PDPs impose stricter utilization management rules more broadly, I estimate the following specification across all drug-formulary combinations:

$$Y_{dft} = \delta_0 + \delta_1 SAandMA_f + \delta_2 MAOnly_f + \delta_3 SAandMA_f \times Opioid_d + \delta_4 MAOnly_f \times Opioid_d + \gamma_t + \gamma_t \times Opioid_d + [\gamma_t \times \alpha_d] + \epsilon_{dft} \quad (2.2)$$

Y_{dft} represents utilization management outcome for drug d listed on formulary f in year t. Outcomes include any utilization management rule, a prior authorization requirement, and a quantity limit restriction. Because maximum daily MED allowance is specific to opioids, I exclude this outcome from the analysis. Equation 2.2 includes year fixed effects (γ_t) fully interacted with an indicator for whether the listed drug is an opioid ($\gamma_t \times Opioid_d$).

The coefficients of interest in Equation 2.2 are δ_1, δ_2, δ_3, and δ_4. δ_1 and δ_2 capture the average difference in utilization management rules for non-opioid drugs listed on SA-PDP and MA-PDP formularies (δ_1) and non-opioid drugs listed on MA-PDP Only formularies (δ_2), relative to non-opioid drugs listed on formularies used exclusively by SA-PDPs. δ_3 and δ_4 capture the average difference in utilization management rules for opioids listed on SA-PDP and MA-PDP formularies (δ_3) and opioids listed on MA-PDP Only formularies (δ_4), relative to the coverage restrictions for non-opioids within formulary types. In addition to the baseline model, I also present estimates from models that include year by drug effects ($\gamma_t \times \alpha_d$) to determine whether differences in utilization management rules exist within coverage for the same year-drug combinations. Standard errors are again clustered at the formulary-level, and I estimate all models via OLS.

Table B.1 presents estimates of δ_1, δ_2, δ_3, and δ_4 from Equation 2.2. Columns 1 and 2 contain estimates from models in which the outcome is any utilization management

rule; columns 3 and 4 contain estimates from models in which the outcome is a prior authorization requirement; and, columns 5 and 6 contain estimates from models in which the outcome is a quantity limit restriction. Odd-numbered columns contain estimates from the baseline model, while even-numbered columns contain estimates from models which include year by drug effects.

On average, non-opioid drugs listed on SA-PDP and MA-PDP formularies are less likely to have a utilization management rule relative to non-opioid drugs listed on formularies used exclusively by SA-PDPs. This is driven by lower rates of prior authorization requirements; the estimate of -0.01 implies a seven percent reduction from the overall mean (14 percent). Conversely, opioids listed on SA-PDP and MA-PDP formularies are seven percentage points more likely to have a utilization management rule relative to non-opioid drugs listed on these formularies. Non-opioid drugs listed on MA-PDP Only formularies are substantially less likely to have a utilization management rule relative to non-opioid drugs listed on SA-PDP Only formularies. The estimate of -0.02 implies a nine percent reduction from the mean of 26 percent. This is driven by a significantly lower likelihood of a quantity limit restriction. Across all outcomes, the inclusion of year by drug effects has minimal impact on either the magnitude or the precision of the estimates. The results offer no evidence that formularies used by MA-PDPs have more restrictive utilization management rules across all drugs relative to formularies used exclusively by SA-PDPs. Rather, drugs listed on formularies used by MA-PDPs are generally less likely to have a corresponding utilization management rule.

2.5.2 Parent Organization Analysis

The analysis thus far has designated Part D formularies as distinct entities. However, Part D formularies are often linked to the same parent organization; these are organizations that oversee the operation of multiple Part D plans. For example, in Figure 2.2 formulary "00008307" and formulary "00008308" are both linked to the same parent or-

ganization ("BlueShield of California"). In this section, I examine whether differences in benefit design persist within formularies linked to the same parent organization. If these differences persist, this finding would imply that parent organizations strategically designate formularies with more restrictive opioid benefit design to MA-PDPs. If these differences do not persist, this could suggest that the main estimates are driven by differences in information across insurance companies, rather than strategic benefit design (Lavetti and Simon, 2018).

To conduct this analysis, I use Part D Plan Enrollment Files through CMS to identify parent organizations associated with each Part D formulary. I limit the sample to formularies that correspond with one parent organization only. This removes from the analysis 26 formularies that are associated with multiple parent organizations (out of 1,105).[2] To test for differences within parent organizations, I re-estimate Equation 2.1 with the inclusion of year by parent organization effects, year by parent organization by ingredient effects, and year by parent organization by drug effects. All estimates are identified off of opioids listed on SA-PDP and MA-PDP formularies and opioids listed on MA-PDP Only formularies that share a parent organization with at least one SA-PDP Only formulary during the same year.

Table B.2 contains estimates of β_1 and β_2 from Equation 2.1. Because the sample of formulary-opioid combinations changes with the removal of 26 formularies from this analysis, I re-estimate Equation 2.1 on the reduced sample. Panel A contains estimates of Equation 2.1 from the reduced sample. Panel B contains estimates of Equation 2.1 with the additional layers of parent organization effects.

The estimates in panel A mirror the estimates from the full sample of formulary-opioid combinations in sign. However, there are several discrepancies in the magnitude and the precision of the estimates. Estimates of β_1 (SA-PDP and MA-PDP) corresponding to models in which the outcomes are any utilization management rule or a quantity limit

[2]These formularies correspond to four percent of the enrolled population.

restriction are smaller in magnitude and less precise than the main estimates. However, they continue to indicate a statistical difference in quantity limit restrictions. Additionally, estimates of β_2 (MA-PDP Only) are smaller in magnitude when the outcome is the natural logarithm of maximum daily MED allowance. However, these estimates remain significant at the one-percent level.

The inclusion of parent organization effects impacts the estimates in several ways. Opioids listed on SA-PDP and MA-PDP formularies remain four percentage points more likely to have a quantity limit restriction relative to opioids listed on SA-PDP Only formularies. However, this estimate is not significant with the inclusion of drug effects. The maximum daily MED allowance corresponding to opioids listed on MA-PDP Only formularies is, on average, now only two percent lower than that of opioids listed on SA-PDP Only formularies with a quantity limit restriction. This estimate is noisy and declines in magnitude with the inclusion of ingredient and drug effects. This imprecision may reflect the fact that there are a limited number of SA-PDP and MA-PDP formularies (42) and MA-PDP Only formularies (152) that share a parent organization with an SA-PDP Only formulary. However, a comparison of the estimates suggests that at least part of the differences in benefit design for opioids may be driven by differences in information across insurance companies.

2.5.3 Benefit Design Over Time

Data years 2008, 2009, 2011, 2013, and 2015 constitute a period of significant change in the medical community's assessment of safe opioid prescribing levels. The changes in utilization management outcomes that occur throughout the sample period reflect an increased awareness of the dangers associated with opioid overprescribing. While the percentage of all drugs with a corresponding utilization management rule increases from 20 percent in 2008 to 30 percent in 2015, the percentage of opioids with a corresponding utilization management rule rises from 25 percent in 2008 to over 80 percent in 2015

(Figure B.1 and Figure B.2). This is largely driven by an increase in quantity limit restrictions for opioids. However, increased quantity limit restrictions are not accompanied by changes in maximum daily MED allowances; while the average maximum daily MED allowance declines somewhat for opioids listed on SA-PDP Only formularies, there is no change in maximum daily MED allowances among opioids listed on formularies used by MA-PDPs.

In this section, I test for differences in benefit design for opioids throughout the sample period by re-estimating Equation 2.1 across individual data years. Estimates of β_1 and β_2 from this analysis are presented in Table B.3. I also present estimates from models that include drug effects in Figure B.3.

Opioids listed on SA-PDP and MA-PDP formularies are significantly more likely to have a quantity limit restriction than opioids listed on formularies used exclusively by SA-PDPs in 2008. The estimate of 0.11 is significant at the five-percent level, and constitutes a 60 percent increase from the mean of 18 percent. This estimate is robust to the inclusion of both ingredient and drug effects. Opioids listed on both SA-PDP and MA-PDP formularies and MA-PDP Only formularies have, on average, a 30 percent lower maximum daily MED allowance relative to opioids listed on SA-PDP Only formularies in 2008. Although the magnitude of these estimates declines with the inclusion of ingredient and drug effects, these estimates remain significant at conventional levels and continue to represent a considerable difference (seven to nine percent).

After 2008, the differences in benefit design for opioids across formulary types dissipate. While opioids listed on SA-PDP and MA-PDP formularies are generally more likely to be subject to a quantity limit restriction, these estimates are noisy. Opioids listed on MA-PDP Only formularies are substantially less likely to have a corresponding quantity limit restriction in 2015; the estimate of -0.13 is significant at the one-percent level, and constitutes a 17 percent decline from the mean of 78 percent during this year. In 2013, the maximum daily MED allowance is, on average, 14 percent higher among opioids

listed on SA-PDP and MA-PDP formularies relative to opioids listed on formularies used exclusively by SA-PDPs; although this estimate is significant at the one-percent level, it is substantially smaller in magnitude and imprecise with the inclusion of ingredient and drug effects. Throughout the data years, the average maximum daily MED allowance corresponding to opioids listed on MA-PDP Only formularies is generally lower than that corresponding to SA-PDP Only formularies. However, the only estimate that is significant at conventional levels is that corresponding to data year 2015 (-0.06).

2.6 Analysis of Propoxyphene Drugs

In a related study, I find that enrollment in an MA-PDP lowered daily dosages of opioids during the years 2008 and 2009 (Rhodes, 2020). Lower dosages during these years were driven by the effect of MA-PDP enrollment on propoxyphene use (brand names Darvon and Darvocet), a high dosage opioid. Although propoxyphene was withdrawn from the market in 2010, the dangerous side-effects associated with propoxyphene use, including risk of overdose and abnormal heart rhythms, were known well in advance of the drug's 2010 withdrawal; the first petition to remove propoxyphene from the market occurred in 1976 (Wilson, 2010). In Rhodes (2020), I find that enrollment in an MA-PDP lowered the probability of propoxyphene use by 76 percent relative to enrollment in an SA-PDP. In this section, I examine whether benefit design served as a mechanism through which MA-PDPs reduced propoxyphene use.

I begin by testing for differences in coverage for any propoxyphene drug across formulary types. For each Part D formulary, I create a binary indicator that equals one if the formulary covered at least one propoxyphene drug and zero otherwise. I collapse the data at the formulary-level, and I estimate the following specification across all formularies:

$$Y_{ft} = \theta_0 + \theta_1 SAandMA_f + \theta_2 MAOnly_f + \gamma_t + \epsilon_{ft} \tag{2.3}$$

Y_{ft} represents coverage outcome for formulary f in year t. In addition to estimating models in which the outcome is any propoxyphene coverage, I also estimate separate models for each opioid ingredient (i.e. any oxycodone drug, any tramadol drug, etc...) to determine whether differences in coverage exist more broadly. Estimates of θ_1 and θ_2 capture the average difference in coverage for a given ingredient across MA-PDP and SA-PDP formularies (θ_1) and MA-PDP Only formularies (θ_2) relative to formularies used exclusively by SA-PDPs. I also estimate models weighted by total Medicare enrollment to determine whether the estimates vary when assigning greater weight to formularies used by a greater population of enrollees. All models are estimated via OLS.

Estimates of θ_1 and θ_2 from Equation 2.3 are presented in Table B.4. For each opioid ingredient, I present estimates from the unweighted model (column 1), as well as estimates from the weighted model (column 2). I also present estimates from the unweighted models in Figure B.4.

SA-PDP and MA-PDP formularies and MA-PDP Only formularies are generally more likely to cover a given opioid ingredient relative to formularies used exclusively by SA-PDPs. In instances where estimates of θ_1 and θ_2 are negative, the estimates are generally noisy and I am unable to rule out a null effect. There are two notable exceptions; MA-PDP Only formularies are less likely to cover any methadone or propoxyphene drug. MA-PDP Only formularies are six percentage points less likely to cover a methadone drug; this represents a six percent decline from the mean rate of coverage for any methadone drug (96 percent). MA-PDP Only formularies were 16 percentage points less likely to cover at least one propoxyphene drug during 2008 and 2009 relative to formularies used exclusively by SA-PDPs; this constitutes an 18 percent reduction from the mean coverage rate for propoxyphene of 88 percent. The estimates from enrollment weighted models are not qualitatively different.

In addition to testing for differences in coverage for any propoxyphene drug, I also examine whether there are differences in benefit design conditional on propoxyphene cov-

erage. In Table B.5, I present estimates of Equation 2.1 stratified by propoxyphene drugs that appear across formularies in 2008 and 2009 and non-propoxyphene opioids that appear across formularies during the same years. Relative to propoxyphene drugs listed on SA-PDP Only formularies, propoxyphene drugs listed on MA-PDP Only formularies are less likely to have a corresponding prior authorization requirement; however, they are more likely to have a quantity limit restriction. Conditional on a quantity limit restriction, the maximum daily MED allowance is, on average, lower among propoxyphene drugs listed on both SA-PDP and MA-PDP formularies and MA-PDP Only formularies. While these estimates are not significant at conventional levels, both estimates increase in magnitude and precision with the inclusion of year by drug effects.

The estimates in Table B.5 indicate similar differences in utilization management rules for non-propoxyphene opioids during the years 2008 and 2009. Non-propoxyphene opioids listed on SA-PDP and MA-PDP formularies are more likely to have a quantity limit restriction relative to non-propoxyphene opioids listed on SA-PDP Only formularies. Conditional on a quantity limit restriction, non-propoxyphene opioids on both SA-PDP and MA-PDP formularies and MA-PDP Only formularies have, on average, a lower maximum daily MED allowance relative to those listed on formularies used exclusively by SA-PDPs. These results suggest that MA-PDPs were more likely to impose utilization management rules across all opioids in 2008 and 2009, and not just on propoxyphene drugs.

2.7 Discussion

This study adds to a literature that examines whether integrated MA-PDPs internalize externalities from prescription drugs. I test the hypothesis that MA-PDPs set more restrictive benefit design for prescription opioids relative to SA-PDPs; because of the breadth of coverage that MA-PDPs provide, these plans have an incentive to consider the link between high dosages of opioids and adverse health events. SA-PDPs face no

such incentive. I find evidence that supports this hypothesis. Relative to opioids listed on formularies used exclusively by SA-PDPs, opioids listed on formularies used by both SA-PDPs and MA-PDPs are more likely to have a quantity limit restriction. Conditional on having a quantity limit restriction, opioids listed on formularies used exclusively by MA-PDPs have lower daily dosage allowances relative to opioids listed on formularies used exclusively by SA-PDPs. Sensitivity analysis indicates that these findings may be partially driven by differences in information across insurance companies. However, these differences do not explain the full effect, suggesting that MA-PDPs strategically design benefits for opioids.

This study also adds to a literature that examines the effect of MA-PDP enrollment on opioid use. In a related study, I find that, relative to enrollment in an SA-PDP, enrollment in an MA-PDP lowered the likelihood of propoxyphene use (Rhodes, 2020). In this study, I find evidence that benefit design may have served as a mechanism through which MA-PDPs reduced propoxyphene use; during the years 2008 and 2009, formularies used exclusively by MA-PDPs were substantially less likely to cover propoxyphene relative to formularies used exclusively by SA-PDPs. In addition, I find that formularies used exclusively by MA-PDPs were less likely to cover methadone, a class of drugs generally used in the treatment of opioid use disorder. This finding may reflect plan efforts to deter enrollees with this condition, although further research on this issue is needed.

Previous literature also finds that, relative to enrollment in an SA-PDP, enrollment in an MA-PDP lowers the likelihood of any opioid use (Baker et al., 2020; Rhodes, 2020). If this effect was driven by benefit design initiatives, it would likely manifest through prior authorization requirements. I find no evidence of differences in prior authorization requirements across formularies used exclusively by SA-PDPs and formularies used by MA-PDPs. This suggests that MA-PDPs lower the likelihood of any opioid use through other mechanisms, such as coordination with providers. Indeed, Baker et al. (2020) find that MA-PDP enrollment lowers the likelihood of receiving a prescription from a high

volume opioid prescriber, suggesting that MA-PDPs may avoid contracting with "riskier" prescribers. Future work should examine the extent to which plans also coordinate with contracted providers to monitor enrollees' opioid use.

This study has several limitations. First, I am unable to distinguish between different types of prior authorization requirements and quantity limit restrictions. Previous literature finds that more restrictive utilization management rules are most effective in reducing opioid use (Morden et al., 2008). To the extent that utilization management rules vary across Part D formularies in terms of strictness, this may differentially impact how effective these rules are in limiting high dosage opioid use.

Second, because formularies often span multiple counties, states, and regions, I am unable to control for geographic characteristics in my empirical approach. If, for example, MA-PDPs are more prevalent in states with increased regulations on opioid use than SA-PDPs, than more restrictive benefit design may be the result of state requirements rather than MA-PDP incentives. However, there are two reasons why geographic differences are unlikely to be driving the results. First, opioid abuse is uncommon among the elderly Part D population. While these formularies may also be linked to the under-65 Medicare population (who are at a higher risk of opioid abuse), it seems unlikely that formularies would be tailored to this population of beneficiaries. Second, I find that differences in benefit design for opioids across MA-PDPs and SA-PDPs is most pronounced in 2008, prior to the onset of many state initiatives.

A third limitation is that it is not well understood how Part D plans choose a formulary. Part D plans (or parent organizations) may develop their own formularies, or, they may coordinate with pharmacy benefits managers (PBMs) to identify a suitable formulary. PBMs, private companies that administer prescription drug benefits, play a prominent role in the Part D program. However, little is know about their coordination with individual Part D plans. Future research should examine the extent to which individual plans design formularies and corresponding utilization management rules.

Figure 2.1: Part D Benefit Design Choices

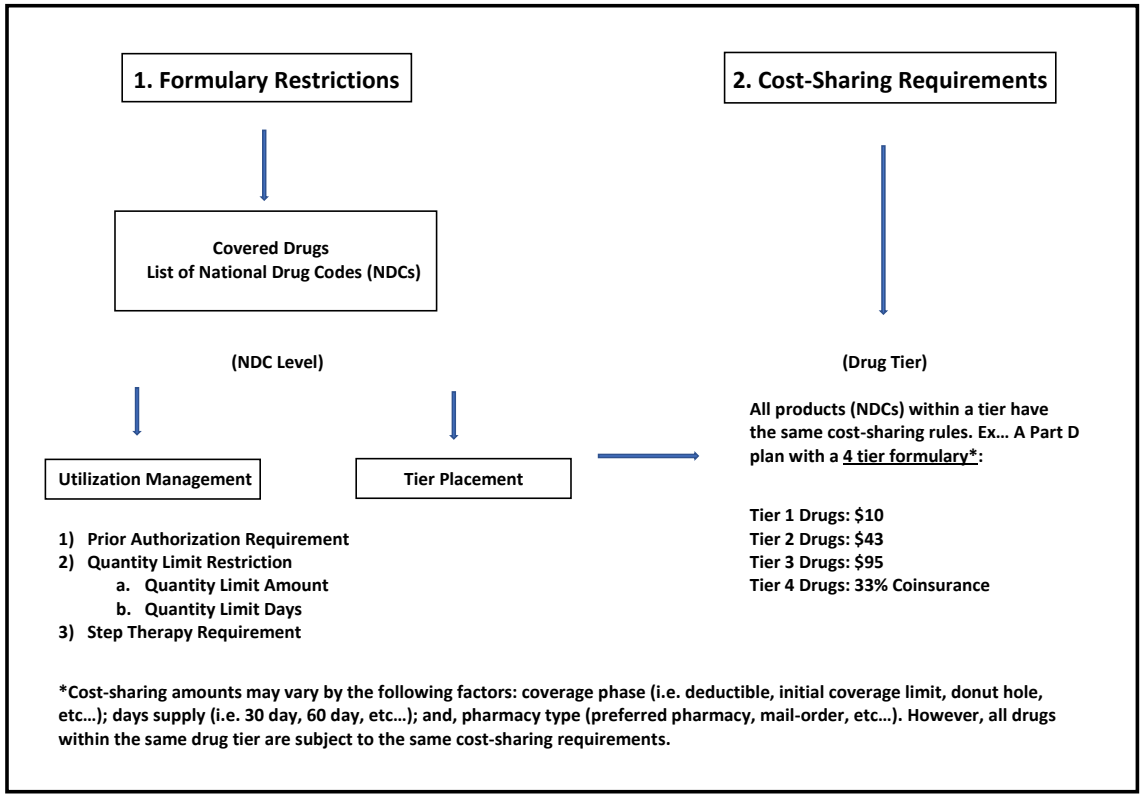


Figure 2.2: Formulary Type Examples (From Data Year 2008)

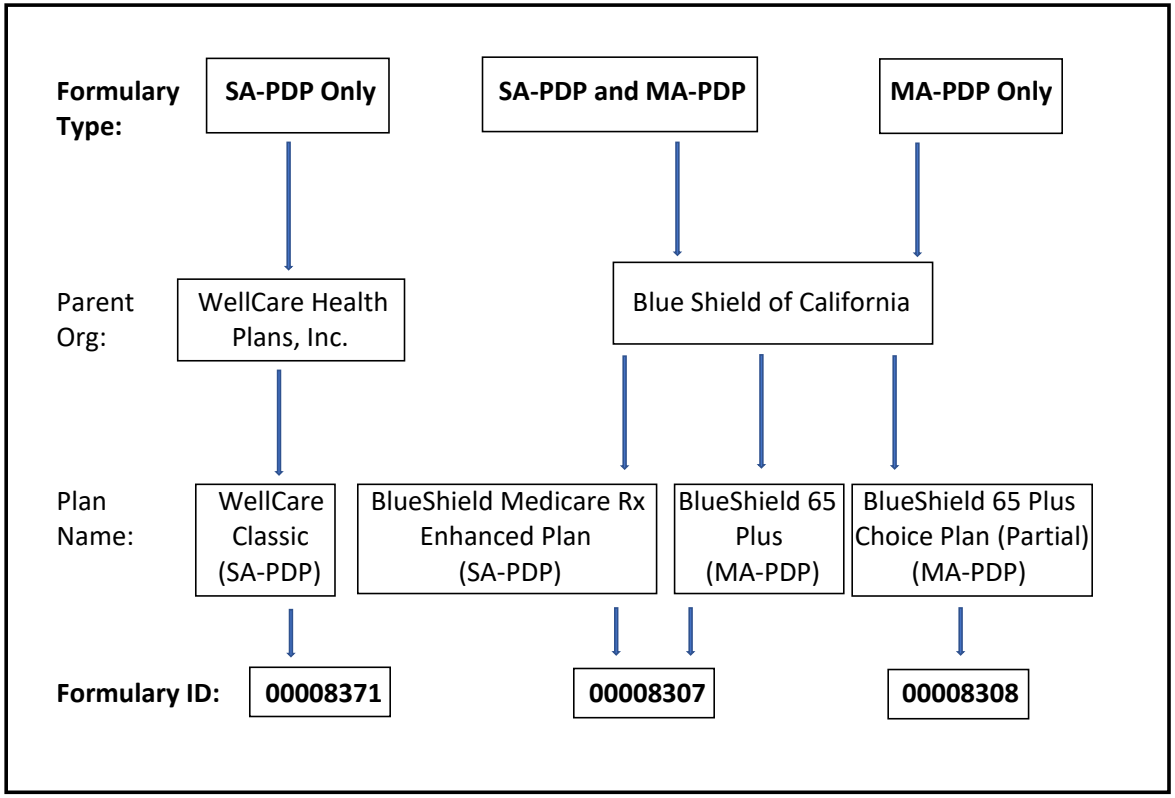
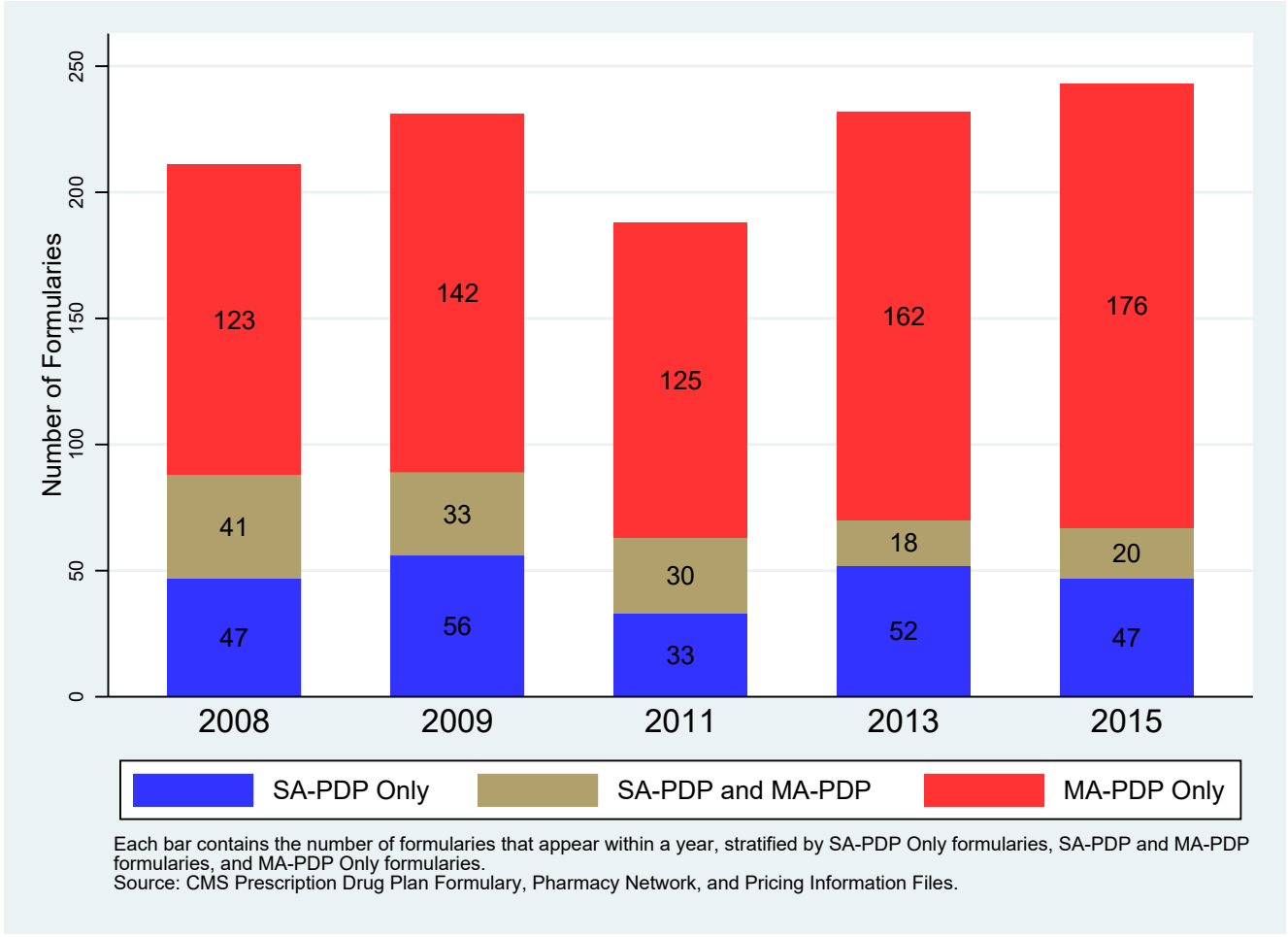
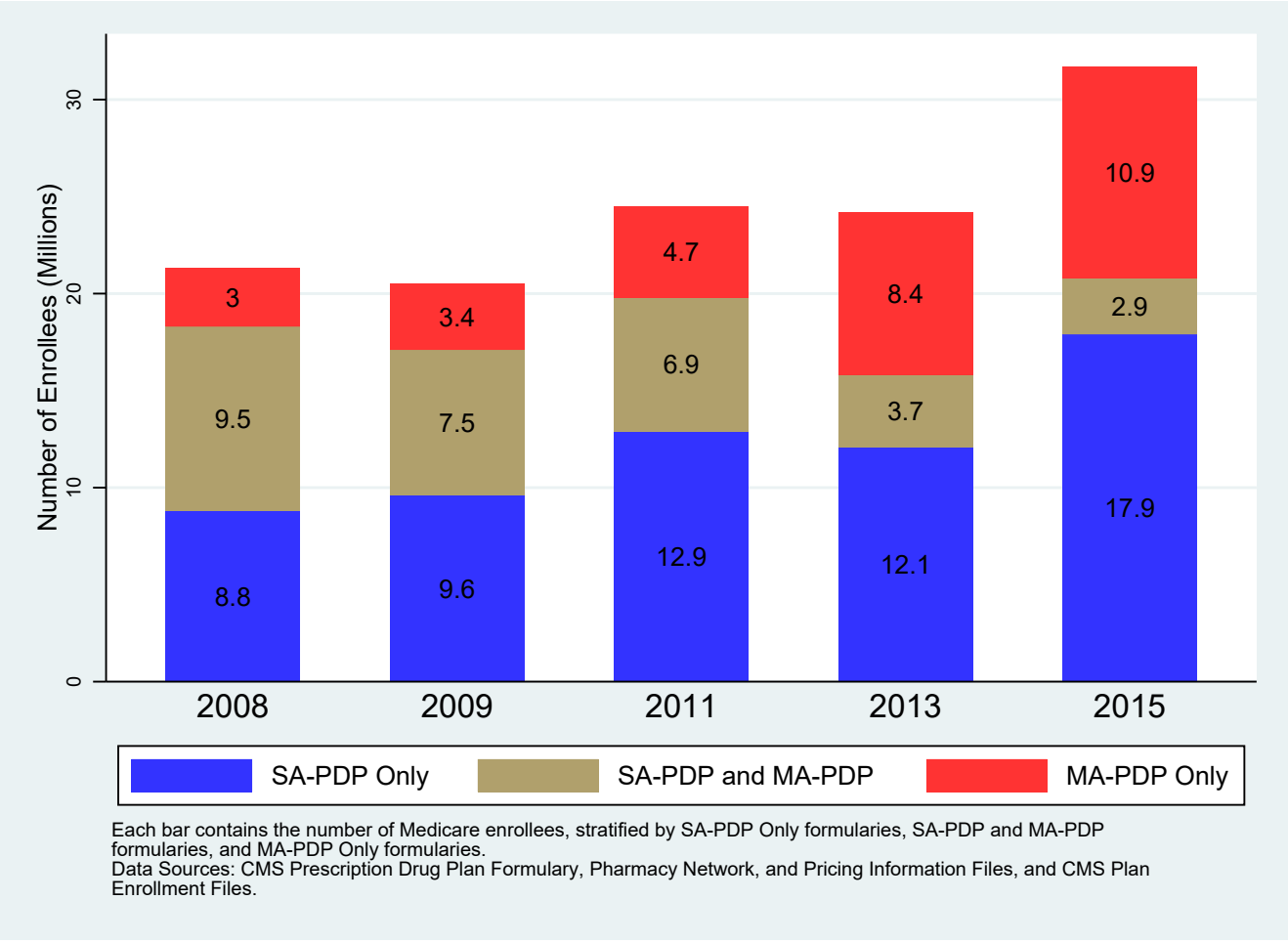


Figure 2.3: Formulary Count by Sample Year



Each bar contains the number of formularies that appear within a year, stratified by SA-PDP Only formularies, SA-PDP and MA-PDP formularies, and MA-PDP Only formularies.
Source: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files.

Figure 2.4: Number of Medicare Enrollees by Sample Year



Each bar contains the number of Medicare enrollees, stratified by SA-PDP Only formularies, SA-PDP and MA-PDP formularies, and MA-PDP Only formularies.
Data Sources: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files, and CMS Plan Enrollment Files.

Table 2.1: Sample Means at the Formulary-Level

	All Formularies (1)	SA-PDP Only (2)	SA-PDP and MA-PDP (3)	MA-PDP Only (4)
Part D Plans	12.4	19.3	27.3	7.3
SA-PDPs	5.7	19.3	12.6	0
MA-PDPs	6.78	0	14.8	7.3
Enrollees	110,544	261,074	214,721	41,633
NDCs	3,705	3,605	3,949	3,689
Opioid NDCs	154	149	178	151
Any Opioid (%)	1	1	1	1
N	1,105	235	142	728

Note: The table reports sample means at the formulary-level.
Sources: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files, and CMS Plan Enrollment Files.

Table 2.2: Sample Means at the Formulary-Drug-Level

	All Formularies	SA-PDP Only	SA-PDP and MA-PDP		MA-PDP Only	
	Mean	Mean	Mean	Diff	Mean	Diff
	(1)	(2)	(3)	(4)	(5)	(6)
A. All Drugs						
Any UM (%)	0.2564	0.2683	0.2459	-0.022[c]	0.2548	-0.013
PA (%)	0.1413	0.1431	0.1253	-0.018[b]	0.1441	0.001
QL (%)	0.1431	0.1544	0.1486	-0.006	0.1383	-0.016[b]
N	4,093,765	847,074	560,774		2,685,917	
B. Opioids						
Any UM (%)	0.4629	0.4417	0.4496	0.008	0.4728	0.031
PA (%)	0.1138	0.1158	0.1219	0.006	0.1114	-0.004
QL (%)	0.4179	0.3916	0.4035	0.012	0.4294	0.038
QL Daily MED*	169.77	177.25	173.96	-3.29	166.71	-10.54[a]
N	170,545	34,942	25,322		110,281	

Notes: The table reports sample means at the formulary-drug-level. Panel A contains sample means for all listed drugs; panel B contains sample means for all listed opioids. Column 1 presents sample means for drugs listed on all Part D formularies; column 2 presents sample means for drugs listed on formularies that are used exclusively by SA-PDPs; column 3 presents sample means for drugs listed on formularies that are used by both SA-PDPs and MA-PDPs; and, column 5 presents sample means for drugs that are listed on formularies that are used exclusively by MA-PDPs. Columns 4 and 6 report differences in means between drugs listed on SA-PDP and MA-PDP formularies (column 4) and MA-PDP Only formularies (column 6) relative to drugs listed on SA-PDP Only formularies. "PA" denotes prior authorization requirement; "QL" denotes quantity limit restriction; and, "QL Daily MED" denotes the maximum daily MED allowance that corresponds with a quantity limit restriction.
Superscripts a, b, and c denote p-values from a difference-in-means hypothesis test (with heteroscedasticity-robust standard errors clustered at the formulary-level). [c]$p< 0.10$, [b] $p< 0.05$, [a] $p< 0.01$.
*Conditional on a quantity limit restriction.
Source: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files.

Table 2.3: Analysis of Opioid Utilization Management Rules

	Any UM			**Prior Authorization**			**Quantity Limit**			**ln(Daily MED)**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SA-PDP & MA-PDP	0.062**	0.058**	0.057**	0.011	0.009	0.003	0.070***	0.067***	0.068***	-0.063**	-0.028	-0.013
	(0.025)	(0.026)	(0.026)	(0.016)	(0.016)	(0.016)	(0.025)	(0.025)	(0.025)	(0.031)	(0.022)	(0.019)
MA-PDP Only	-0.016	-0.016	-0.017	-0.0128	-0.0101	-0.0098	-0.011	-0.012	-0.013	-0.058***	-0.041***	-0.033***
	(0.019)	(0.019)	(0.019)	(0.0092)	(0.0088)	(0.0087)	(0.019)	(0.019)	(0.019)	(0.022)	(0.013)	(0.012)
Outcome Mean*	0.4630	0.4630	0.4630	0.1138	0.1138	0.1138	0.4179	0.4179	0.4179	169.77	169.77	169.77
Year FEs	X			X			X			X		
Year x Ing FEs		X			X			X			X	
Year x NDC FEs			X			X			X			X
Observations	170,545	170,545	170,545	170,545	170,545	170,545	170,545	170,545	170,545	71,263	71,263	71,263

Notes: The table reports estimates of β_1 (SA-PDP & MA-PDP) and β_2 (MA-PDP Only) from Equation 2.1. The sample includes prescription opioids that appear throughout the data years. Columns 1, 2, and 3 present estimates from models in which any utilization management (UM) rule is the outcome; Columns 4, 5, and 6 present estimates from models in which the outcome is a prior authoization requirement; columns 7, 8, and 9 present estimates from models in which the outcome is a quantity limit restriction; and, columns 10, 11, and 12 present estimates from models in which the outcome is the natural logarithm of the maximum daily morphine equivalent dosage (MED) allowance, conditional on a quantity limit restriction. Columns 1, 4, 7, and 10 include year fixed effects; columns 2, 5, 8, and 11 include ingredient by year effects (ex..."oxycodone X 2011"); and, columns 3, 6, 9, and 12 include year by NDC effects. Standard errors are clustered at the formulary level. *p< 0.10, ** p< 0.05, *** p< 0.01.

*The means corresponding to Daily MED are not log-transformed.

Source: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files.

CHAPTER III

Changes in the Utilization of Mental Health Care Services and Mental Health at the Onset of Medicare

3.1 Introduction

Nearly all U.S. citizens become eligible for Medicare coverage at age 65. Because of this, Medicare has been referred to as "Nearly Universal Health Insurance Coverage," and a recent proposal for single-payer health care in the U.S. has been termed "Medicare for all" (Card et al., 2008; berniesanders.com, 2020). The discrete onset of Medicare eligibility results in an exogenous shock to health insurance coverage rates at age 65. This minimizes many of the selection issues that are often apparent in health insurance settings, and presents a unique opportunity to examine the interaction between health insurance and health outcomes.

Previous research has found that the onset of Medicare is accompanied by increases in the utilization of several types of health care (Decker, 2005; Card et al., 2008). This study furthers this literature by testing the impact of changes in health insurance coverage at age 65 on the utilization of mental health care services and mental health. Using a nationally representative sample, changes in three outcomes are considered: financial barriers to mental health care, visits with mental health professionals, and self-reported mental health.

This study makes several contributions to the existing literature. First, for many individuals, qualifying for Medicare represents a transition from uninsured to insured status. As a result, this study provides insight on the causal effect of health insurance coverage on mental health care utilization and mental health. Previous literature has found that the uninsured are less likely to receive treatment for mental disorders than individuals with health insurance coverage (Cooper-Patrick et al., 1999; Druss et al., 2000; McAlpine and Mechanic, 2000). It is unclear, however, if the previously uninsured would change their utilization of mental health services upon gaining coverage, holding all else constant. This relationship is generally difficult to identify; experiments that randomize coverage status across individuals are costly and difficult to conduct, and population-wide exogenous shocks to health insurance coverage do not commonly occur in natural settings (Levy and Meltzer, 2008). The identification strategy employed in this study, a regression discontinuity design, facilitates credible causal inference.

Second, although previous studies find that the prevalence of mental illness tends to decline with age, increased access to mental health care may still be of benefit to the elderly (Kessler et al., 2005; Neighbors et al., 2007). A 2009 report found that more than 6.5 of the 35 million Americans aged 65 or older suffer from depression (Duckworth, 2009). A better understanding of the interaction between Medicare coverage and mental health care could lead to more efficient and improved treatment.

Third, this study furthers our understanding of the relationship between socioeconomic status and mental health. Previous research documents a strong link between the prevalence of mental illness and lower socioeconomic status (Kessler et al., 2005; Neighbors et al., 2007; Donisi et al., 2013). However, these studies generally focus on the non-elderly population. This study examines if the correlation between mental health and socioeconomic status persists among the elderly, and whether universal health insurance coverage alters these patterns. To examine this relationship, all analysis is conducted on samples that are stratified by education level to test for heterogeneous treatment effects across

socioeconomic groups.

In a preview of the findings, this study documents changes in health insurance coverage rates at age 65 that are consistent with previous studies (Decker, 2005; Card et al., 2008). Individuals from lower socioeconomic backgrounds experience large gains in Medicare coverage, corresponding with an increase in the probability of having any health insurance coverage. Individuals from higher socioeconomic backgrounds also exhibit significant increases in Medicare coverage rates; however, this change is accompanied by reductions in private insurance. The overall gains in coverage are associated with a decrease in the probability of needing mental health care but not obtaining such care because of prohibitive costs. This effect is greatest among individuals from lower socioeconomic backgrounds. Despite this finding, there is no significant change in mental health visits upon reaching Medicare eligibility; however, estimates corresponding to mental health visits are imprecise, and large changes relative to pre-Medicare levels cannot be ruled out, especially among individuals from lower and middle socioeconomic groups. No changes in self-reported mental health are identified at age 65.

3.2 Background and Previous Findings

This study examines if changes in the utilization of mental health care services and mental health accompany the changes in health insurance coverage rates that occur at the onset of Medicare. This research question relates to several strands of literature. The first examines changes in health care utilization after becoming eligible for Medicare coverage. The second investigates the relationship between cost-sharing requirements and mental health care utilization. The third examines the impact of health insurance on mental health.

3.2.1 Medicare Coverage

Two studies have tested for discontinuous changes in health care utilization at the age 65 Medicare eligibility threshold (Decker, 2005; Card et al., 2008). The closest study to this one is Card et al. (2008), who use data from the National Health Insurance Survey for the years 1992-2003 to test for discontinuous changes in health care utilization and health outcomes. They find that individuals from lower socioeconomic groups have more doctors' visits and are less likely to delay care upon reaching Medicare eligibility. Among higher socioeconomic groups, gaining Medicare eligibility is associated with an increase in elective surgeries, such as hip and knee replacements. Decker (2005) uses 11 years of data from the Behavioral Risk Factor Surveillance System and finds that mammography screening rates increase at age 65, especially among women from lower socioeconomic backgrounds.

Other studies have employed individual-level panel data to examine how utilization patterns change after becoming eligible for Medicare coverage. These studies generally document increased health care utilization, especially among the previously uninsured (McWilliams et al., 2003, 2007). McWilliams et al. (2003) find increased use of basic medical services, such as cholesterol testing, mammograms, and prostate examinations, among Medicare eligible individuals who were previously uninsured. McWilliams et al. (2007) find increased doctors' visits and hospitalizations among previously uninsured Medicare eligible individuals who suffer from chronic conditions such as cardiovascular disease and diabetes.

There are several reasons why the findings from previous studies may not translate to mental health care utilization at age 65. First, services such as mammography screenings and prostate examinations have been widely promoted in recent years to the elderly and the near-elderly, unlike outpatient mental health care. Second, individuals approaching the age of Medicare eligibility may prioritize other types of costlier and more involved

care, such as hip and knee replacements. And third, Medicare coverage for outpatient mental health care has historically required higher levels of cost-sharing than other types of care.

In Medicare's original form, Congress modelled coverage for outpatient mental health care in accordance with private insurance coverage at the time. This involved higher copayments and increased coverage restrictions than the requirements for many forms of physical health care (Frank and Glied, 2006). This lack of parity was driven by concerns over the demand response for mental health care; namely, the perception that such care was "discretionary," and coverage requirements on par with other medical services would induce a "cost control" problem (Frank and McGuire, 2000). As a result, Medicare required 50 percent copayments for outpatient mental health care, as compared to the 20 percent copayments required for general medical care.

Lack of parity under Medicare remained until 2010. In 2008, Congress passed the Medicare Improvements for Patients and Providers Act (MIPPA), which required Medicare to begin covering a larger share of the cost of outpatient mental health services beginning in 2010, and to phase in additional increases over time. Under MIPPA, copayments for outpatient mental health care were reduced as follows; dropping from 50 percent to 45 percent beginning in 2010, down to 40 percent in 2012, to 35 percent in 2013, and down to 20 percent in 2014 and thereafter (Ostrow and Manderscheid, 2010).

3.2.2 Cost-Sharing and the Use of Mental Health Services

Although copayments for outpatient mental health care under Medicare have historically been higher than those required for physical health care, gaining coverage at age 65 still results in a reduction in mental health cost-sharing requirements for many individuals, including the previously under-insured and uninsured. Prior studies that examine the link between cost-sharing requirements and outpatient mental health care utilization have found mixed results (Frank and McGuire, 1986; Manning et al., 1986; Goldman et al.,

2006; Ndumele and Trivedi, 2011). Evidence from the Rand Health Insurance Experiment suggests that price sensitivity plays an important role in utilization patterns; study participants who were randomized into plans that covered 100 percent of care were twice as likely to obtain any ambulatory mental health care as participants who faced a 95 percent coinsurance rate (Manning et al., 1986). Conversely, Goldman et al. (2006) find that federal employees did not increase their utilization of mental health and substance-abuse services after parity for these benefits was introduced.

There has been limited research on how cost-sharing requirements affect outpatient mental health care use among the elderly. Ndumele and Trivedi (2011) is a notable exception; the study finds that utilization of mental health services is uncommon among individuals who are enrolled in Medicare managed care plans, and that increasing or decreasing copayments for these services has little effect on utilization patterns. Although the study examines individuals who are 65 years of age and older, these results may not extend to the general Medicare population given the differences in access to care across managed care and traditional fee-for-service plans (Elliott et al., 2011; Martino et al., 2016).

3.2.3 Health Insurance and Mental Health

The onset of Medicare could affect mental health through several channels. For the previously uninsured, gaining coverage at age 65 facilitates increased access to the health care system. For the previously under-insured, transitioning onto Medicare may reduce cost-sharing requirements. Both reductions in cost-sharing requirements and changes in coverage status could increase utilization of mental health services, potentially leading to improvements in mental health. Gaining Medicare coverage may also facilitate increased access to other types of care that lead to improvements in mental health, such as prescription medication (Ayyagari and Shane, 2015).

Since health insurance serves as a safe-guard against high future unexpected health

care costs, gaining coverage at age 65 may also reduce stress and improve mental health, regardless of any changes in utilization. This resonates with findings from the Oregon Health Insurance Experiment; in this ongoing study, previously uninsured individuals who gained Medicaid coverage through a randomized lottery reported higher levels of happiness, an increased connectedness with the health care system, and a reduction in self-reported rates of depression (Finkelstein et al., 2012).

3.3 Data and Methods

This study uses data from the Person File and Sample Adult components of the 2006-2013 National Health Insurance Surveys (NHIS). Person File data contain responses from everyone in a family selected to participate in the NHIS. Among other topics, participants answer questions regarding their age, their race and ethnicity, their health insurance status, and their education. The Sample Adult file is comprised of a subset of individuals from the Person File component; one adult from each family is chosen at random to answer additional questions relating to their health care utilization, their health conditions, and their behavior.

Answers to several questions from the Sample Adult component of the NHIS form the key outcomes used in this analysis. To assess perceived financial barriers to mental health care, participants were asked if there was any time during the past 12 months that they needed mental health care or counseling but did not receive it because they could not afford the costs of care. To gauge mental health care utilization, participants were asked if they had seen or spoken to a mental health professional during the past 12 months. Mental health professionals listed include psychiatrists, psychologists, psychiatric nurses, and clinical social workers. The Kessler K6 nonspecific distress scale is used as a proxy for mental health.

The Person File data contain several key age fields, including birth month, birth year,

and age in years at the time of the interview; an age-in-quarters field is constructed from these fields.[1] Following Card et al. (2008), the analysis begins by limiting the sample to survey respondents who are between the ages of 55 and 74. After merging the Person File and Sample Adult components, limiting the sample to adults between the ages of 55 and 74, and dropping a small fraction of observations with missing entries, the final sample consists of 55,586 observations.

Table 3.1 shows descriptive statistics of the sample; overall demographic, regional, and educational characteristics appear in the top panel, while health insurance, employment, and mental health outcomes are stratified by age group in the bottom panel. The sample means for insurance coverage and employment status suggest stark differences between those aged 55 to 64 and individuals between 65 and 74. The percent of individuals who saw a mental health professional during the past year is 3.4 percentage points lower among the older age group. The fraction of respondents who needed mental health care but did not obtain such care because of costs decreases with age; less than 1 percent of individuals over 65 report this outcome. Kessler K6 scores decline, dropping from 2.6 among 55- to 64-year-olds to 2 among individuals between the ages of 65 and 74. These scores align with previous studies that document declining rates of mental illness beginning with individuals in their late-twenties and early-thirties (Kessler et al., 2005; Neighbors et al., 2007).

3.3.1 Data Analytic Procedures

Equation 3.1 is estimated to test for changes in health insurance coverage rates, the utilization of mental health care services, and mental health at age 65.

[1] More detail on the construction of the age-in-quarters field is presented in section C.2.

$$Y_i = \beta_0 + \beta_1(AgeQ_i - 260) + \beta_2(AgeQ_i - 260)^2 + \beta_3 D65_i + \beta_4(AgeQ_i - 260) \times D65_i + \beta_5(AgeQ_i - 260)^2 \times D65_i + X_i^T\beta + \epsilon_i \quad (3.1)$$

Y_i represents outcomes of interest, including respondent i's health insurance coverage, access to mental health care, and K6 scores. $AgeQ_i$ is respondent i's age-in-quarters. 260 (4*65) is subtracted from the age-in-quarters field to allow for ease of interpretation. β_3 is the coefficient of interest and captures the average treatment effect at the onset of Medicare eligibility at age 65 (and zero quarters). Quadratic age-in-quarters terms allow for curvature on either side of the age 65 cutoff. The term X includes controls for sample year, as well as a vector of covariates that may be correlated with age and the outcome fields, including gender, region, race, ethnicity, and education level.

Because the data derive from a complex national survey, all observations contain sample weights, primary sampling units, and stratum identification. Sample weights are included in all analyses to allow for nationally representative estimates; they inflate each observation by adjusting for non-response and over-sampling, and by incorporating U.S. census population estimates of age, gender, race, and ethnicity. Data years 2006-2013 all derive from the same NHIS sample design, which facilitates proper variance estimation in pooled analysis (CDC, 2016). All analysis incorporates survey design estimation features, including adjustments for subpopulation variance estimates. Models are estimated via ordinary least squares; Equation 3.1 thus represents a linear probability model when modelling all outcomes except for those that pertain to the K6 index.

3.4 Results

3.4.1 Health Insurance Coverage

Table 3.2 contains discontinuity estimates for health insurance outcomes at age 65. Odd-numbered columns contain the mean of each outcome for 64-year-olds; even-numbered columns present the discontinuity estimate (β_3) from Equation 3.1. In addition to presenting results from the overall sample of adults aged 55 to 74 years of age, Table 3.2 also includes age 64 means and estimates of β_3 when the sample is stratified by level of education. These estimates correspond with graphs A.-C. in Figure 3.1.

The discontinuity estimates on the entire sample of 55- to 74-year-olds show that health insurance coverage rates increase by 9.8 percentage points at age 65. This represents an 11 percent increase in coverage rates from the age 64 mean of 88.1 percent. In addition to changes in overall coverage rates, there are also shifts in types of coverage at age 65. The probability of being on Medicare increases by 65.5 percentage points, while the probability of having private coverage decreases by 10.2 percentage points.

There are heterogeneous effects across education groups. While 92.1 percent of 64-year-olds with at least some college education are insured, only 71.6 percent of 64-year-old high school dropouts have any form of coverage. This finding aligns with previous age 65 discontinuity studies that document higher uninsurance rates among lower socioeconomic groups prior to the age 65 threshold (Decker, 2005; Card et al., 2008). The largest gains in coverage occur among high-school dropouts; this group exhibits a 22.1 percentage point increase in coverage rates, which represents a 31 percent increase from the age 64 mean. Coverage rates increase by 8.8 percentage points among high school dropouts and 6.9 percentage points among those with some college.

All three education groups exhibit large gains in Medicare coverage rates at age 65, ranging from a 56.3 percentage point increase among high school dropouts to a 68.9 percentage point increase among individuals with some college education. The overall

decline in private coverage rates is driven by an 8.5 percentage point drop among high school graduates and a 13.9 percentage point decline among individuals with at least some college education. The estimate of 0.04 among high school dropouts implies that private insurance coverage rates do not change for this group, although this estimate is noisy.

The health insurance discontinuity estimates highlight that changes in coverage rates among high school graduates and individuals with some college result from both gaining Medicare coverage and shifting out of private plans. Transitioning from private insurance to Medicare may affect mental health care utilization if private plans offer differing access to provider networks or cost-sharing requirements. As a result, mental health discontinuity estimates that correspond to these groups may capture both the impact of gaining health insurance coverage for the previously uninsured and the effect of transitioning from private coverage onto Medicare. Changes in coverage rates among high school dropouts are driven by gaining Medicare coverage, and not simultaneously dropping private insurance.

3.4.2 Mental Health Care Utilization and Mental Health

Table 3.3 contains discontinuity estimates for outcomes on the utilization of mental health care services and mental health at age 65. Age 64 means and estimates of β_3 are again stratified by level of education below the results for the entire sample. These estimates correspond with graphs D.- F. in Figure 3.1.

Overall, 1.7 percent of 64-year-olds report the need but inability to obtain mental health care because of the costs of such care. High school dropouts report the highest rates of prohibitive costs at 2.8 percent at age 64, while rates for high school graduates and those with at least some college are both below 2 percent. The discontinuity estimates imply that the onset of Medicare has a significant impact on reducing these prohibitive costs. Across all 55-74-year-olds there is a drop of 0.9 percentage points, which represents 57 percent of the age 64 mean. High school dropouts report a statistically significant 2.4 percentage point decrease. The estimates for high school graduates and individuals with

at least some college are -0.9 and -0.7 respectively. The estimate for high school dropouts is not significant, while the estimate for those with at least some college is significant at the 10-percent level.

Just over 7 percent of 64-year-olds saw a mental health professional during the past year. When stratified by level of education, the age 64 means and the illustrations in Figure 3.1.E. show that visit rates are highest among individuals with at least some college education, in accordance with other studies that document higher outpatient utilization rates among the insured population (Cooper-Patrick et al., 1999; Druss et al., 2000; McAlpine and Mechanic, 2000). High school dropouts and high school graduates exhibit similar age 64 utilization patterns, both just below 5 percent. The overall discontinuity estimate suggests that the onset of Medicare is accompanied by a small increase of 0.3 percentage points, although this estimate is imprecise. The discontinuity estimates for high school dropouts and high school graduates are 0.9 and 1.1 percentage points respectively, constituting over a 20 percent increase in visit rates from the age 64 means for both groups. However, neither of these estimates is significant. Individuals with some college education exhibit a small decrease in visit rates, but this estimate is again noisy.

Estimates and means of the K6 index appear in the final two columns of Table 3.3. Age 64 means and Figure 3.1.F. align with findings from previous literature that documents a strong correlation between socioeconomic status and mental health (Kessler et al., 2005; Neighbors et al., 2007; Donisi et al., 2013). Furthermore, the figure suggests that this relationship persists past the onset of Medicare eligibility. High school dropouts report an average K6 score of 3.5 at age 64, while the mean K6 score for individuals with at least some college is almost half of that score. The discontinuity estimates indicate no significant change in K6 outcomes at age 65. Across all 55-74-year-olds the estimate is 0.09; this finding holds for high school dropouts and individuals with at least some college, while high school graduates report an increase in K6 scores of 0.1. None of the discontinuity estimates pertaining to K6 scores are significant.

Beginning in 2010, copayments for outpatient mental health care were progressively lowered from 50 percent under Medicare Part B, eventually reaching 20 percent in 2014. Table 3.4 presents mental health care discontinuity estimates stratified by pre- and post-MIPPA implementation data years. The discontinuity estimates suggest that the gradual lowering of cost-sharing requirements through MIPPA has not generated significant changes in visits or prohibitive costs at the age 65 threshold. Although the sign of the estimate for individuals with at least some college education changes when the outcome is mental health visits, the findings across the MIPPA-implementation time-periods are not statistically different (P = 0.7). The only pair of estimates that are statistically different across time-periods occurs among individuals with at least some college education when the outcome is prohibitive mental health care costs (P = 0.03). These individuals report a greater decline in prohibitive costs at the onset of Medicare in the pre-MIPPA implementation period than is reported in the post-MIPPA implementation years.

3.5 Sensitivity Analyses

Additional analyses are conducted to confirm the validity of the results.

3.5.1 Changes in Employment

A critical component of the discontinuity analysis is that no other changes occur at the onset of Medicare eligibility that could simultaneously affect mental health outcomes. Given that many individuals are retiring around this age, significant changes in employment at the age 65 threshold could confound the analysis. For example, recent retirees may have more time to focus on health, and a lower opportunity cost of accessing providers. Furthermore, individuals may elect to retire upon turning 65 because they no longer require the same levels of private coverage. Although previous studies have ruled out changes in employment at age 65, these studies involved data from before the

Great Recession, which may have altered retirement decisions (Rust and Phelan, 1997; Card et al., 2008). Columns 1 and 2 in Table C.1 contain age 64 means and discontinuity estimates for employment. The estimates are not significant, and the implied changes are minor relative to the observed changes in health insurance coverage status in Table 3.2.

3.5.2 Changes in Rates of Serious Mental Illness

Although estimates from models where the K6 index is the outcome of interest indicate no changes in self-reported mental health, these findings may not capture the impact among individuals at the tail of the distribution. To examine this, K6 scores that are greater than or equal to 13 are also considered as an outcome. Scores of this magnitude have been shown to correspond with serious mental illness (Kessler et al., 2003). Table 3.1 indicates that rates of individuals with these scores are low; 4.2 percent of individuals between the ages of 55 and 64 had a score of 13 or more, while only 2.4 percent of 65-74-year-olds report scores of this magnitude. Furthermore, individuals who are 55-64 years of age who obtained a score of 13 or more have lower health insurance coverage rates (82 percent) than individuals in the same age group who obtained a score below 13 (88 percent).

Columns 3 and 4 in Table C.1 present the age 64 means and discontinuity estimates when the outcome is binary and equal to one for K6 scores of 13 or more. High school dropouts have the highest rates of these scores at 7.1 percent, while only 3.1 percent of 64-year-old high school graduates and 1.7 percent of individuals with at least some college report scores of 13 or more. The overall discontinuity estimate suggests that rates of these scores increase at age 65 across all 55-74-year-olds by 0.9 percentage points. This estimate is significant at the 10 percent level ($P = 0.09$). All three education groups exhibit increases at age 65, ranging from 0.7 percentage points among the highest education group to 1.4 percentage points among high school dropouts. However, none of the estimates on the stratified samples are statistically significant. These results confirm that the onset of

Medicare is not accompanied by immediate improvements in self-reported mental health.

3.5.3 Alternative Specification and Age Window

The regression discontinuity design emphasizes the impact at the threshold, under the assumption that individuals on either side of the age 65 cutoff are extremely similar, except for their eligibility for Medicare coverage. In selecting an appropriate age window, there is a trade-off between bias and precision. Observations closer to the cutoff are more comparable, yet limiting the sample to individuals just above and below the age 65 threshold reduces the sample size. Including additional observations further from the cutoff increases power, but raises concerns that these observations differ along dimensions other than insurance status. This often necessitates the inclusion of higher-order polynomials in the running variable, as seen in Equation 3.1.

Given the large sample size, additional analysis is conducted using a narrower age window and a specification that imposes less reliance on functional form. This analysis limits the sample to individuals within 3 years of the age 65 threshold, between the ages of 62 and 67. The local linear model that is estimated equates to Equation 3.1 without the inclusion of the quadratic age-in-quarters terms that correspond with β_2 and β_5.

Table C.2 compares the original mental health outcome estimates against estimates from the linear specification with a narrower age window.[2] The findings are very similar across models and all estimates overlap within a reasonable degree of confidence. However, there are some discrepancies. While the overall finding of a reduction in prohibitive costs is roughly 1 percentage point across both models, the estimate is greater in magnitude and statistically significant among high school graduates when estimating the effect on the narrower age window. The estimate corresponding to mental health visits among high school dropouts is again positive at the onset of Medicare, while the estimate on visits

[2]Health insurance coverage discontinuity estimates are extremely similar across the two models. These results are available upon request.

among high school graduates declines in this model. Again, neither estimate is significant. K6 estimates are generally consistent across models, although estimates that correspond to the linear specification are much noisier than the estimates from Equation 3.1, likely driven by the smaller sample size.

Despite these discrepancies, the comparisons in Table C.2 largely confirm the conclusions drawn from the findings presented in Table 3.3; at the age 65 threshold, mental health visit rates and self-reported mental health do not change significantly, while there is evidence that the rate at which individuals face financial barriers to mental health care declines.

3.5.4 Alternative Stratification

In addition to stratifying by level of education, analysis is conducted on a sample that is stratified into terciles based on pre-65 health insurance coverage characteristics. This facilitates a more balanced observation count across samples, and confirms that stratifying by level of education accurately captures the impact across groups with varying pre-65 coverage rates.

To establish these terciles, a probit model is estimated on the probability of having any insurance coverage on the sample of individuals who are between the ages of 55 and 64. All covariates from Equation 3.1 are included in this model. The results are presented in Table C.3. Predicted probabilities of having any health insurance coverage are then generated from these results on the entire sample of 55-74-year-olds. The sample is stratified into terciles based on these predicted probabilities.

Table C.4 contains mental health outcome discontinuity estimates from Equation 3.1 when the sample is stratified into these terciles. Individuals from tercile 1 possess demographic characteristics that are associated with higher uninsurance rates prior to Medicare eligibility. At age 64, these individuals report the highest rates of financial barriers to care, the lowest rates of mental health visits, and the highest K6 scores. These individuals

exhibit a significantly estimated 2 percentage point reduction in financial barriers to care at age 65. Individuals from tercile 2 also report a 1 percentage point reduction in financial barriers to care; this estimate is significant at the 10 percent level. None of the estimates corresponding to mental health visits or K6 scores are significant. These results generally align with the findings from Table 3.3.

3.6 Discussion

This study adds to a literature that investigates the immediate impact of Medicare eligibility on health care utilization by testing whether the changes in coverage rates that occur at age 65 correspond with changes in the utilization of mental health care services and mental health. Overall, there is no significantly estimated change in mental health visits or K6 scores; however, at age 65 there is a 57 percent decline from the age 64 rate in the probability of needing mental health care but not obtaining such care because of prohibitive costs.

The overall estimates mask heterogeneity across level of education. High school graduates and individuals with at least some college education show gains in health insurance coverage rates at age 65. However, the overall gains are accompanied by declines in private coverage rates. As a result, it is difficult to attribute changes in mental health outcomes to gaining Medicare coverage; dropping private insurance coverage may also have an impact on these outcomes. Despite this, it is worth noting that both groups exhibit declining rates of prohibitive costs, although the findings are somewhat sensitive to the estimation strategy. Future research should examine whether transitioning from private coverage onto Medicare affects cost-sharing requirements and utilization patterns at age 65.

Because of their pre-65 characteristics, high school dropouts are most likely to be affected by gaining health insurance through the onset of Medicare. Prior to turning 65, individuals from this group exhibit the highest rates of uninsurance, are more likely to

forgo treatment for mental health conditions because of costs, obtain the highest average K6 scores, and report the lowest mental health visit rates. Additionally, changes in coverage rates among high school dropouts are driven by gaining Medicare coverage, and not simultaneously dropping private insurance. Previous age 65 discontinuity studies have found the largest impact of Medicare coverage on health care utilization among high school dropouts. These studies find effects that are both large in magnitude and precisely estimated (Decker, 2005; Card et al., 2008).

Relative to the age 64 rate, high school dropouts report a large decline in the probability of not being able to obtain mental health care due to prohibitive costs. This estimate is sensitive to the age window and specification; however, alternative analysis confirms that individuals who are more likely to lack insurance coverage prior to turning 65 also report a significant decline in this outcome. The estimate on mental health visits among high school dropouts is imprecise, and the null of no change in visits cannot be rejected. However, this estimate is best interpreted in the context of other discontinuity studies, where there is a clear and significant increase in utilization patterns among high school dropouts identified at age 65. The cost-sharing reductions that occurred through the implementation of MIPPA have not generated significant changes in either of these outcomes among high school dropouts. There is no estimated change in K6 scores, and the graphical analysis shows that high school dropouts continue to report the highest average K6 scores after becoming eligible for Medicare coverage. There is, however, evidence that these scores are declining with age.

There are several reasons that could explain why high school dropouts report lower prohibitive costs but no significantly estimated change in visits. First, the estimate on visits corresponds to changes on the extensive margin, and does not capture intensity of use. Reductions in prohibitive cost-sharing may signify increased utilization among those who visited a mental health professional. This outcome would not be reflected in the estimate corresponding to mental health visits.

Second, the question regarding prohibitive costs in the NHIS survey does not specify mental health visits as the lone source of care. The onset of Medicare has been linked to increased utilization of other types of health care, including doctors' visits (Card et al., 2008). It is common for individuals to obtain behavioral health care through primary care physicians, especially given their ability to prescribe medications that treat mental illness (Olfson, 2016). As a result, the estimate on prohibitive costs may capture increased access to other types of care that facilitate treatment for mental illness. Again, this would not be reflected through changes in visit patterns.

Third, although gaining Medicare coverage may lower cost-sharing requirements, obtaining care is contingent on access to mental health professionals and their acceptance of Medicare patients. This may not be the case. For example, a recent study found that psychiatrists are less likely to accept Medicare as a form of payment relative to physicians in other specialties (Bishop et al., 2014). Because of this, individuals may report an increased ability to afford the costs of mental health care, despite facing other barriers to such care.

Further research exploring these potential explanations would be useful. Additionally, although the discontinuity estimates across all three education groups suggest no change in mental health visits at age 65, these estimates are imprecise and large effects relative to age 64 means cannot be ruled out, especially among high school dropouts and high school graduates. Future research that evaluates whether additional factors can explain this imprecision would be useful. For example, location of residence, including living in a mental health shortage area, could contribute to the noise in these estimates. Unfortunately, the publicly-available NHIS data does not facilitate this level of analysis.

This study has several limitations. The outcomes that pertain to mental health care involve a one-year recollection period. Because of this, 65-year-olds may recall mental health care visits and prohibitive costs from before they were eligible for Medicare coverage. However, previous discontinuity studies have relied on similarly phrased questions;

the analysis in Card et al. (2008) involves a one-year recollection period, while the analysis in Decker (2005) involves a two-year recollection period. Both studies found significant changes in utilization patterns among high school dropouts at age 65. It is unclear why recollection of access to mental health care would differ from recollection of other types of care.

Additionally, this analysis tests only for discontinuous changes at age 65. Newly enrolled Medicare beneficiaries may require more time to familiarize themselves with mental health coverage benefits. This limitation extends to the findings regarding reductions in cost-sharing requirements through the implementation of MIPPA. Although the estimates suggest little effect from the changes thus far, these findings capture the impact at the age 65 threshold and do not reflect changes in overall utilization patterns among all Medicare enrollees. Furthermore, the analysis is limited to data years 2006-2013; full parity for outpatient mental health care under Medicare did not come into effect until 2014. And finally, although no change in K6 scores is found at the Medicare eligibility threshold, gaining health insurance coverage and increased access to the health care system may induce changes in mental health over a longer time-horizon.

Figure 3.1: Changes in Health Insurance Coverage and Mental Health Outcomes at Age 65

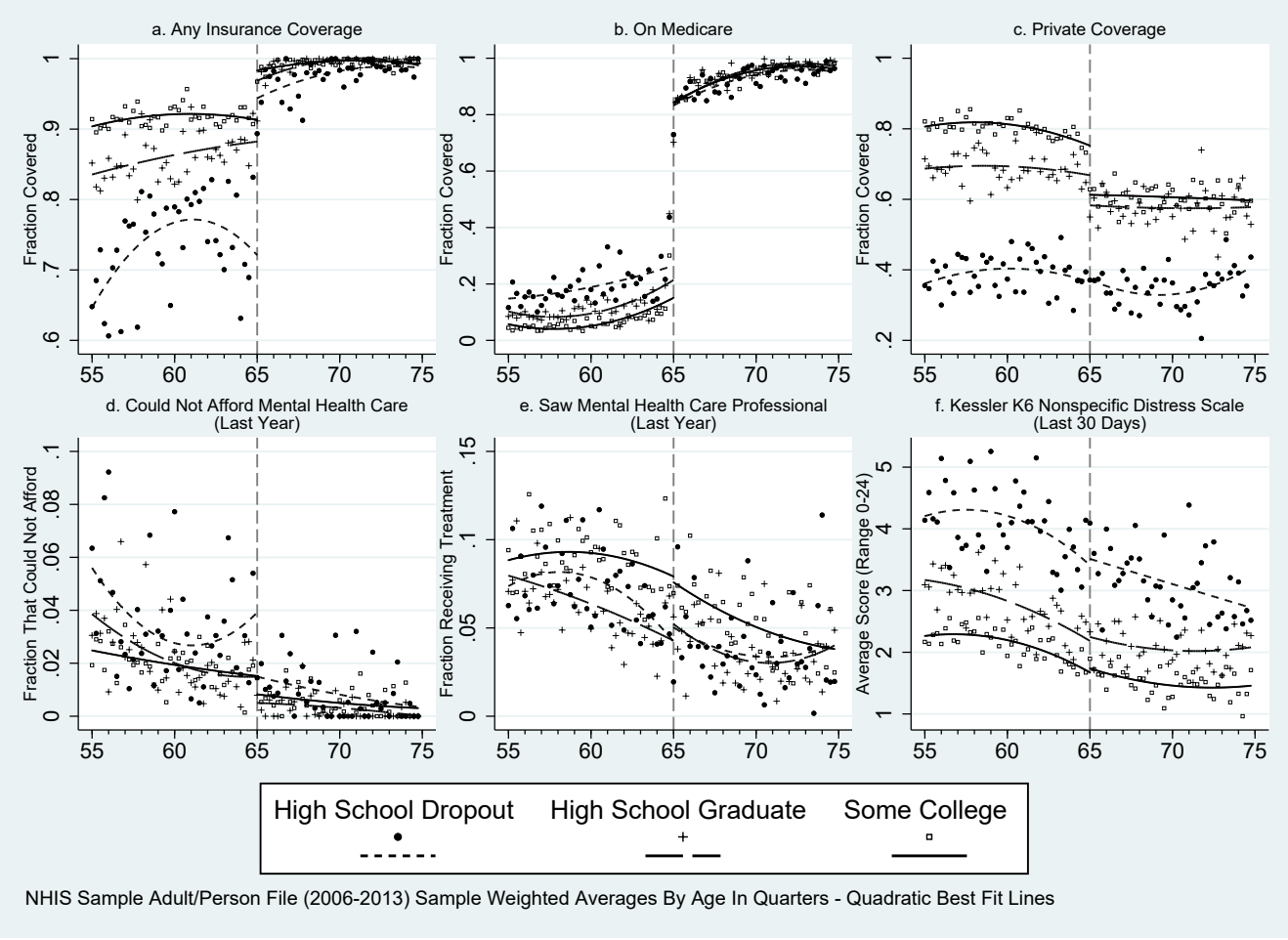


Table 3.1: Sample Characteristics of Adults Ages 55-74, NHIS 2006-2013

Variable	Weighted Means	
Demographic		
White	85.2%	
Black	10.2%	
Hispanic	8.3%	
Female	52.5%	
Age	63.35	
Regional		
Midwest	23.2%	
Northeast	18.2%	
South	37.3%	
West	21.3%	
Education		
High School Dropout	15.0%	
High School Graduate	28.8%	
At Least Some College	56.2%	
	55-64 Years Old	*65-74 Years Old*
Insurance		
Any Insurance	87.9%	98.9%
Medicare Coverage	9.4%	93.1%
Private Coverage	72.0%	55.0%
Employment		
Employed	59.4%	23.6%
Mental Health Care		
During the last year...		
Could Not Afford Mental Health Care	2.3%	0.5%
Saw Mental Health Professional	8.0%	4.6%
Psychological Distress		
During the last 30 Days...		
K6 Score (0-24)	2.58	2.00
K6 $\geq$ 13 (Serious Mental Illness)	4.20%	2.40%
N (55,586)	32,746	22,840

Note: Data derive from the 2006-2013 Person File and Sample Adult components of the National Health Insurance Survey (NHIS).

Table 3.2: Age 64 Means and Estimated Insurance Discontinuities, NHIS 2006-2013

Outcome:	Any Insurance		On Medicare		Private Coverage	
	Age 64 Mean (1)	RD Estimate (2)	Age 64 Mean (3)	RD Estimate (4)	Age 64 Mean (5)	RD Estimate (6)
Overall (Adults Aged 55-74)	88.11	9.76***	18.51	65.49***	68.28	-10.19***
(N = 55,586)		(0.82)		(1.19)		(1.34)
Level of Education						
High School Dropout	71.62	22.14***	27.58	56.25***	35.64	0.04
(N = 9,760)		(2.75)		(2.92)		(4.03)
High School Graduate	88.49	8.81***	20.75	63.51***	67.95	-8.46***
(N = 15,703)		(1.49)		(2.14)		(2.76)
At Least Some College	92.13	6.99***	15.15	68.95***	76.76	-13.94***
(N = 30,123)		(0.90)		(1.53)		(1.69)

Notes: Odd-numbered columns contain the sample-weighted average among 64-year-olds. Even-numbered columns contain estimates of β_3 from Equation 3.1. Linearized standard errors appear in parentheses below the estimates. All models are fit to data years 2006-2013 of the NHIS Sample Adult and Person File data. ***Statistically significant at the 1 percent level; **Statistically significant at the 5 percent level; *Statistically significant at the 10 percent level.

Table 3.3: Age 64 Means and Estimated Mental Health Discontinuities, NHIS 2006-2013

Outcome:	Did Not Get Mental Health Care Last Year (Costs)		Mental Health Visit Last Year		Kessler K6 [0-24]	
	Age 64 Mean (1)	RD Estimate (2)	Age 64 Mean (3)	RD Estimate (4)	Age 64 Mean (5)	RD Estimate (6)
Overall (Adults Aged 55-74) (N = 55,586)	1.71	-0.98*** (0.34)	7.32	0.29 (0.77)	2.18	0.09 (0.12)
Level of Education						
High School Dropout (N = 9,760)	2.80	-2.37** (1.09)	4.83	0.99 (1.47)	3.53	0.09 (0.39)
High School Graduate (N = 15,703)	1.97	-0.88 (0.63)	4.77	1.09 (1.28)	2.31	0.11 (0.24)
At Least Some College (N = 30,123)	1.32	-0.70* (0.39)	9.15	-0.25 (1.17)	1.77	0.09 (0.13)

Notes: Odd-numbered columns contain the sample-weighted average among 64-year-olds. Even-numbered columns contain estimates of β_3 from Equation 3.1. Linearized standard errors appear in parentheses below the estimates. All models are fit to data years 2006-2013 of the NHIS Sample Adult and Person File data. ***Statistically significant at the 1 percent level; **Statistically significant at the 5 percent level; *Statistically significant at the 10 percent level.

Table 3.4: Estimated Mental Health Care Discontinuities By Pre- and Post-MIPPA Implementation, NHIS 2006-2013

Outcome:	Did Not Get Mental Health Care Last Year (Costs)			Mental Health Visit Last Year		
	2006-2009 RD Estimate (1)	2010-2013 RD Estimate (2)	Test of Equality (3)	2006-2009 RD Estimate (4)	2010-2013 RD Estimate (5)	Test of Equality (6)
Overall	-1.24**	-0.78*	(P = 0.466)	0.42	0.20	(P = 0.881)
	(0.49)	(0.43)		(1.13)	(0.97)	
N	22,085	33,501		22,085	33,501	
Level of Education						
High School Dropout	-2.09	-2.55*	(P = 0.832)	1.19	0.92	(P = 0.929)
	(1.66)	(1.43)		(1.97)	(2.19)	
N	4,195	5,565		4,195	5,565	
High School Graduate	-0.12	-1.64*	(P = 0.21)	0.37	1.76	(P = 0.553)
	(0.83)	(0.91)		(1.79)	(1.69)	
N	6,591	9,112		6,591	9,112	
At Least Some College	-1.74***	-0.02	(P = 0.03)	0.33	-0.63	(P = 0.664)
	(0.62)	(0.49)		(1.91)	(1.35)	
N	11,299	18,824		11,299	18,824	

Notes: Columns (1) and (4) contain estimates from NHIS data years 2006-2009. Columns (2) and (5) contain estimates from NHIS data years 2010-2013. Linearized standard errors appear in parentheses below each estimate. Sample size appears below standard errors. Columns (3) and (6) contain p-values from a test of equality of β_3 (from Equation 3.1) across models. ***Statistically significant at the 1 percent level; **Statistically significant at the 5 percent level; *Statistically significant at the 10 percent level.

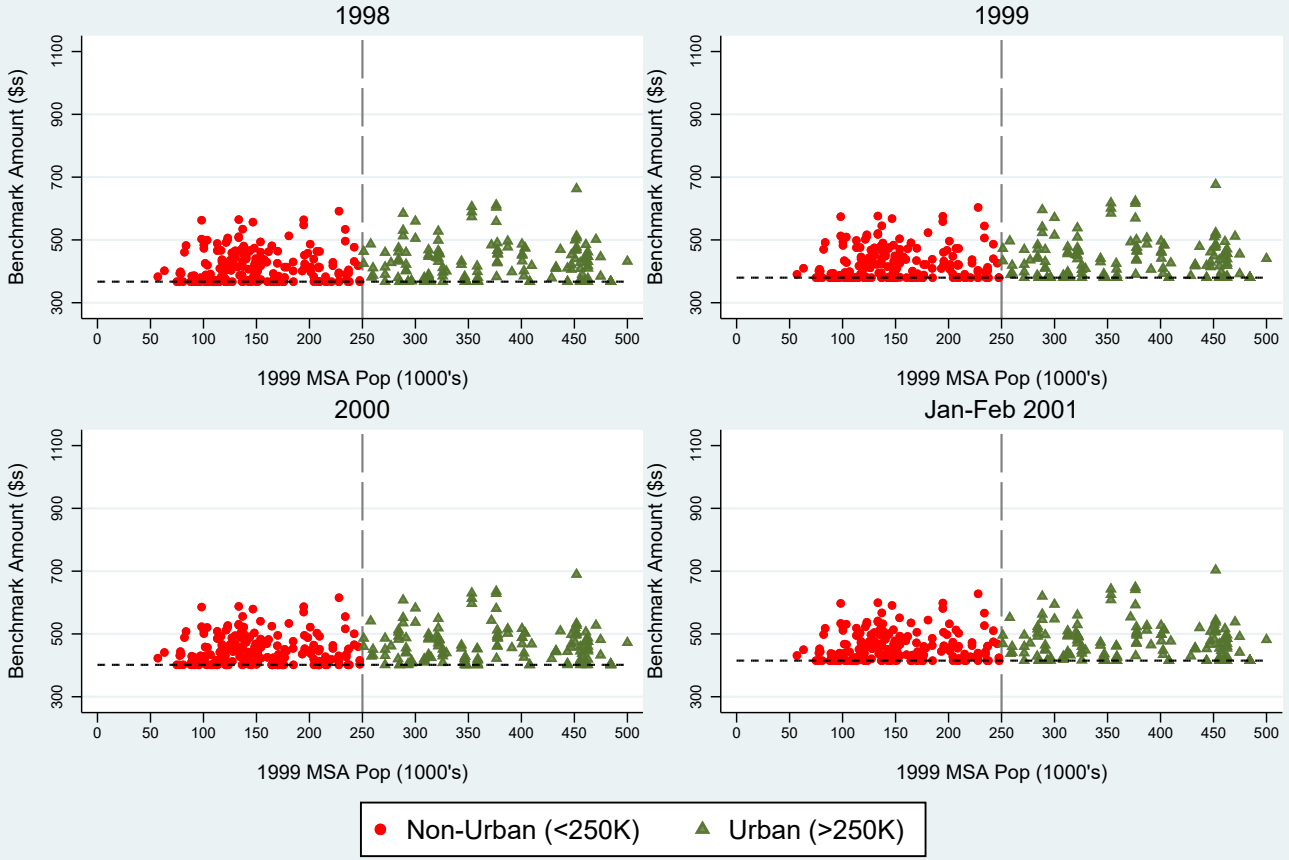
APPENDICES

APPENDIX A

Appendix to Private Health Insurer Incentives and Prescription Opioid Use: Evidence from Medicare Part D

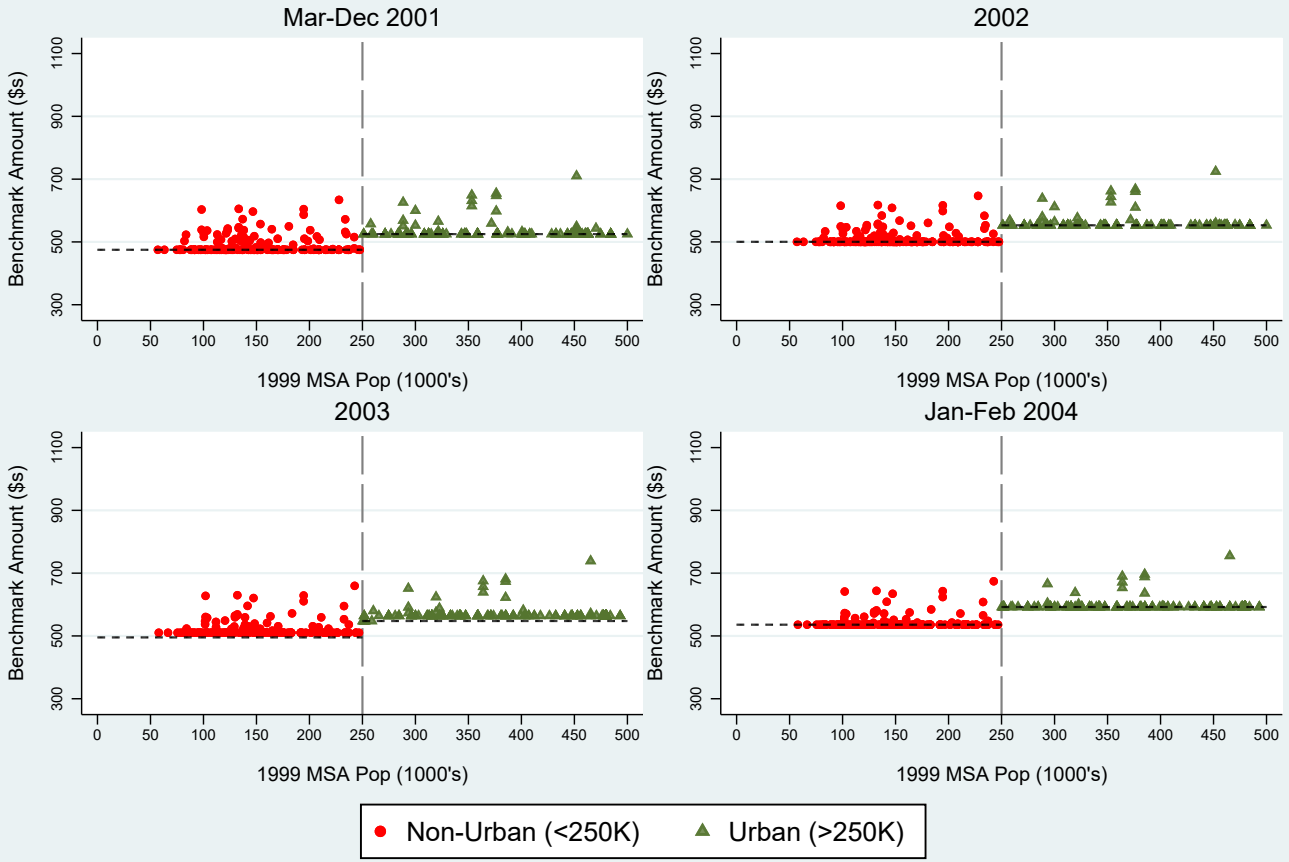
A.1 Supplemental Figures

Figure A.1: 1998 - February 2001 County Benchmark Figures by Statistical Area Population



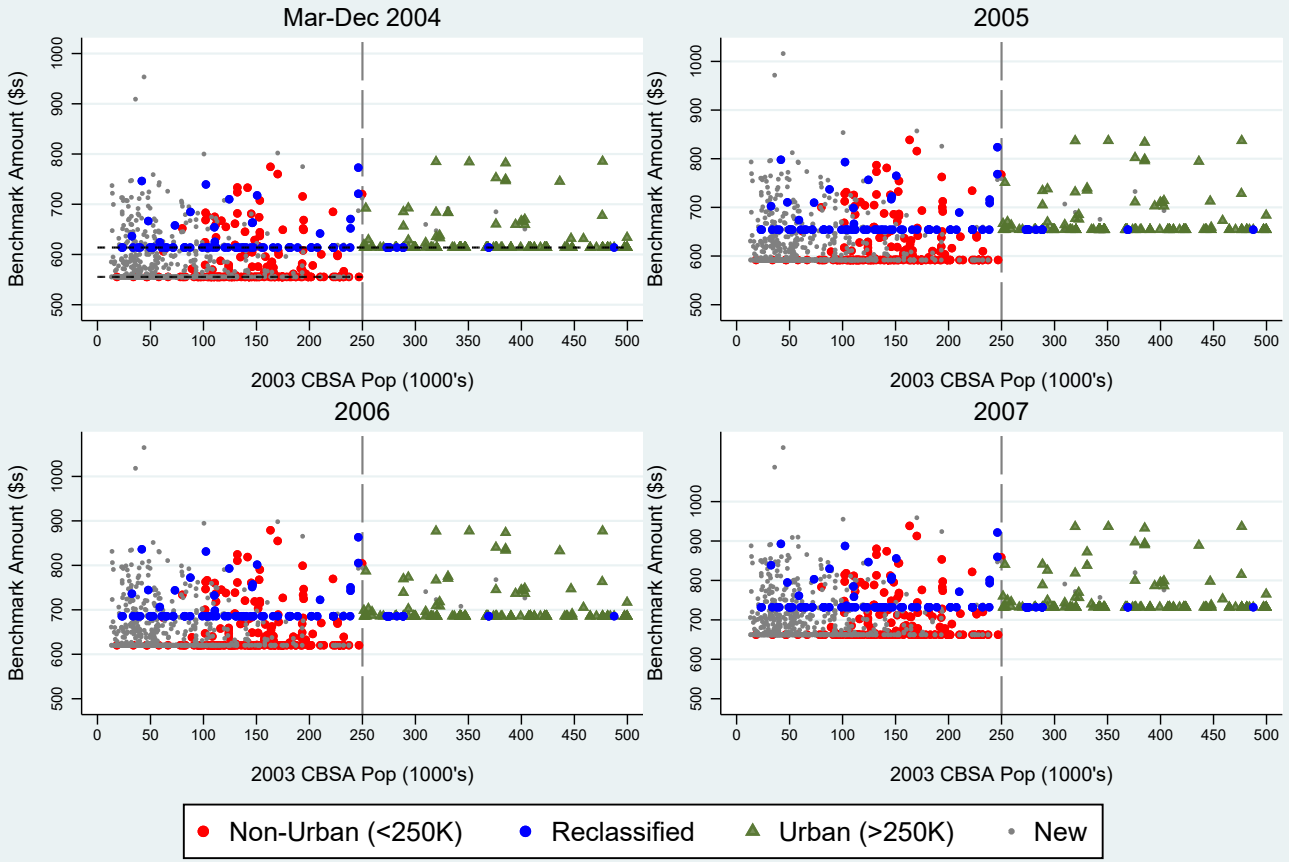
Notes: Each point represents a county. Lines indicate floor levels.
Sources: Census MSA-County Delinieation Files, Census Population Estimates, and CMS Ratebook and Calculation Data.

Figure A.2: March 2001 - February 2004 County Benchmark Figures by Statistical Area



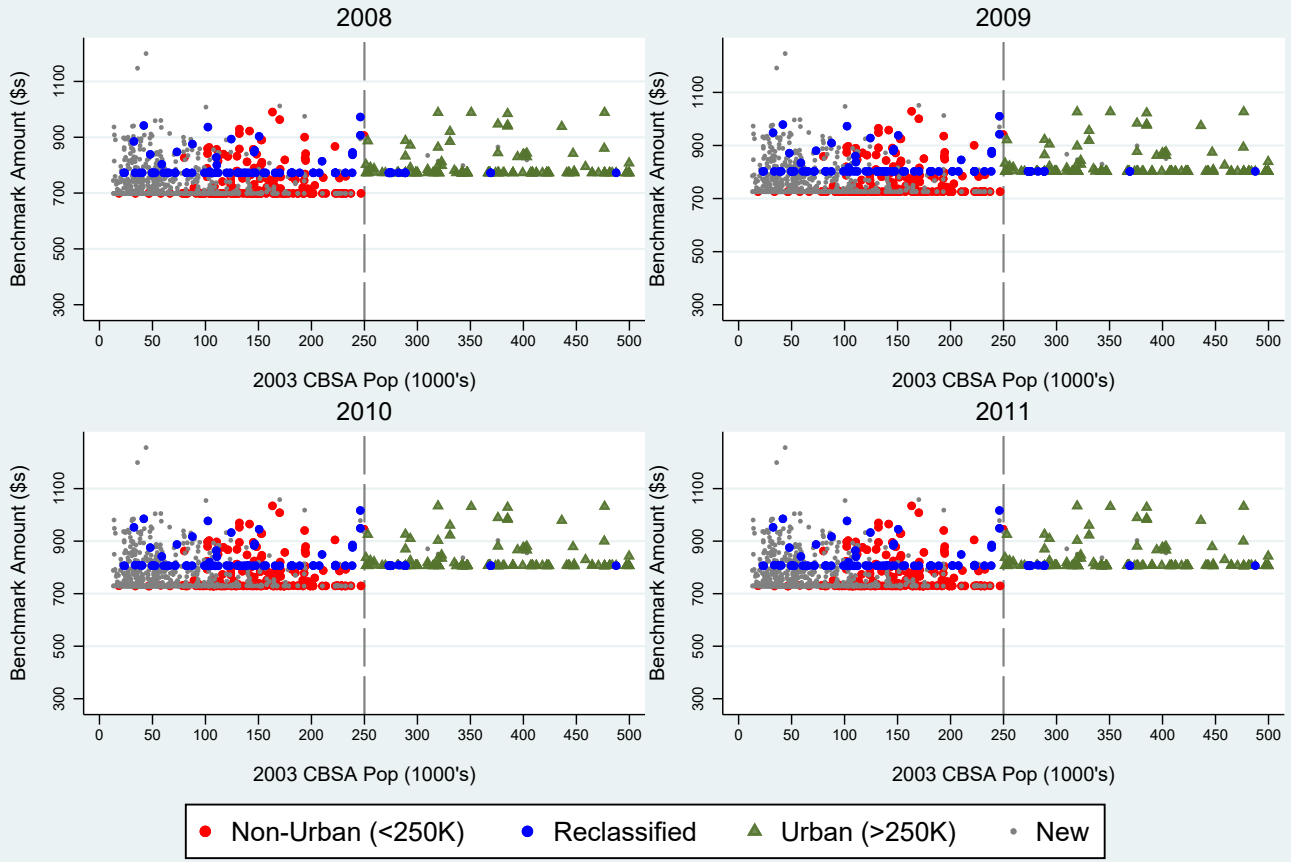
Notes: Each point represents a county. Lines indicate floor levels.
Sources: Census MSA-County Delinieation Files, Census Population Estimates, and CMS Ratebook and Calculation Data.

Figure A.3: March 2004 - 2007 County Benchmark Figures by Statistical Area



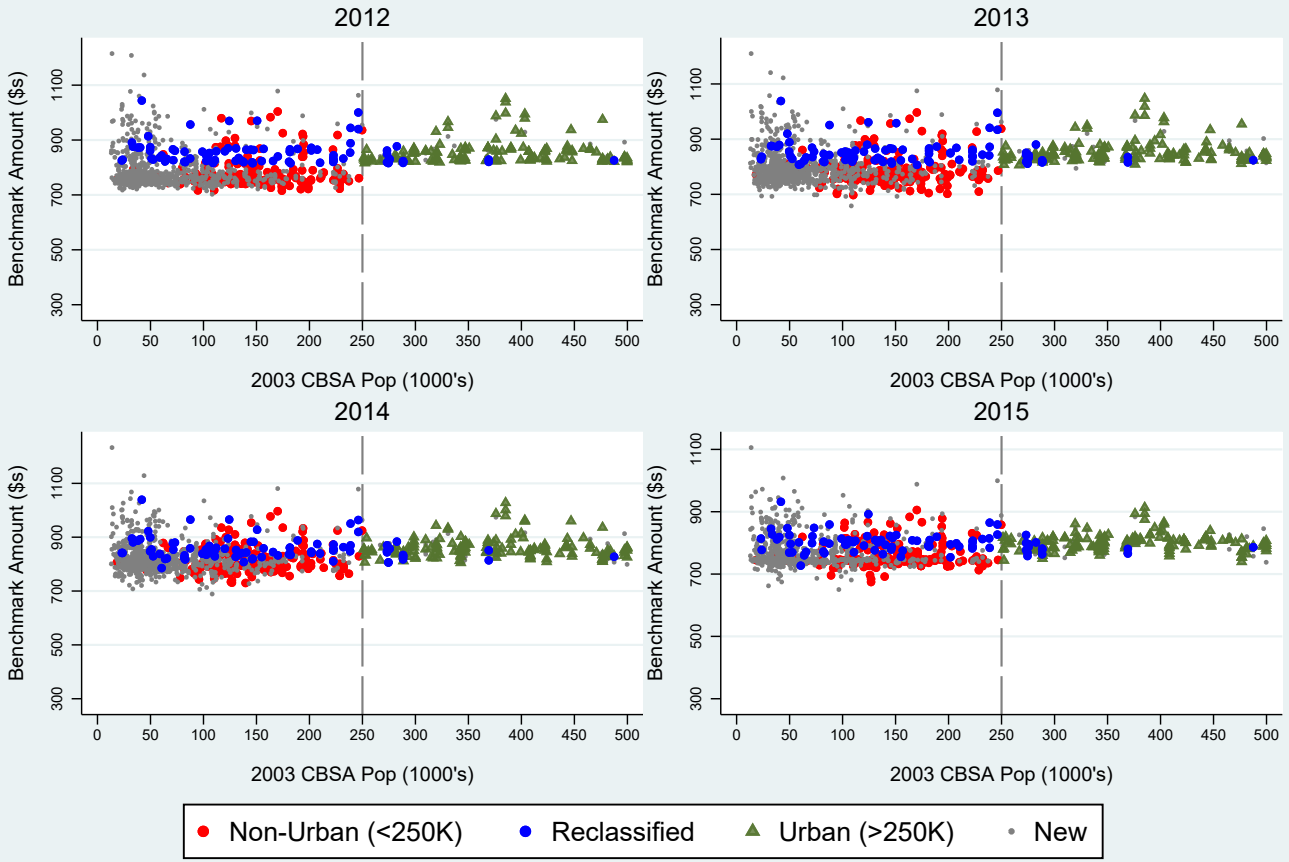
Notes: Each point represents a county. Lines indicate floor levels.
Sources: Census MSA-County Delinieation Files, Census Population Estimates, and CMS Ratebook and Calculation Data.

Figure A.4: 2008 - 2011 County Benchmark Figures by Statistical Area



Notes: Each point represents a county.
Sources: Census MSA-County Delinieation Files, Census Population Estimates, and CMS Ratebook and Calculation Data.

Figure A.5: 2012 - 2015 County Benchmark Figures by Statistical Area



Notes: Each point represents a county.
Sources: Census MSA-County Delinieation Files, Census Population Estimates, and CMS Ratebook and Calculation Data.

A.2 Supplemental Tables

Table A.1: Sample Restrictions

	2008	2009	2010	2011	2012	2013	2014	2015	**N**
Beneficiaries	9,690,866	9,914,675	10,157,679	10,492,180	10,717,786	11,209,016	11,550,386	12,347,813	**86,080,401**
Not Enrolled in Part D	36,303	34,833	31,665	34,297	34,683	39,786	46,392	0	**257,959**
Remaining Beneficiaries	9,654,563	9,879,842	10,126,014	10,457,883	10,683,103	11,169,230	11,503,994	12,347,813	**85,822,442**
Current Reason Not Age	1,633,183	1,712,453	1,798,498	1,892,616	1,957,791	2,039,519	1,855,004	1,905,919	**14,794,983**
Original Reason Not Age	2,236,994	2,319,482	2,412,953	2,520,543	2,600,418	2,706,833	2,779,318	2,912,565	**20,489,106**
Dual Eligibles	1,907,584	1,955,281	2,038,690	2,130,191	2,144,038	2,200,917	2,276,242	2,452,554	**17,105,497**
LIS Recipients	2,160,660	2,208,061	2,297,588	2,381,340	2,416,240	2,512,449	2,592,296	2,784,597	**19,353,231**
Partial Part D Coverage	1,476,716	1,470,677	1,540,882	1,513,440	1,577,580	1,630,003	1,737,014	1,931,847	**12,878,159**
Death	400,876	393,718	402,854	411,529	416,016	428,727	433,048	486,019	**3,372,787**
Remaining Beneficiaries	5,432,328	5,574,642	5,678,945	5,870,214	5,974,149	6,316,246	6,513,213	7,020,554	**48,380,291**
Data Cleaning Drops	1,874,854	1,903,066	1,902,951	1,739,924	1,817,468	1,295,969	1,198,530	1,242,785	**12,975,547**
Final Cohort	3,557,474	3,671,576	3,775,994	4,130,290	4,156,681	5,020,277	5,314,683	5,777,769	**35,404,744**

Note: Table depicts sample restrictions. Final column contains the number of remaining observations after sample drops.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table A.2: Morphine Milligram Equivalents Conversion Table

Opioid Active Ingredient	**Morphine Equivalents per Milligram**
Butorphanol	7
Codeine	
Tablet, Capsule, Solution, or Suspension	0.15
Injection	0.25
Dihydrocodeine	0.25
Fentanyl*	
Lozenge or Tablet	0.13
Nasal Spray	0.16
Mucosal Spray or Film	0.18
Injection or Cartridge	0.3
Patch	7.2
Hydrocodone	1
Hydromorphone	
Oral or Rectal	4
Cartridge or Injection	20
Levorphanol	11
Meperidine	
Oral Solution or Tablet	0.1
Cartridge or Injection	0.3
Methadone	4
Morphine	
Oral or Rectal	1
Cartridge or Injection	3
Nalbuphine	3
Opium	1
Oxycodone	1.5
Oxymorphone	3
Pentazocine	0.37
Propoxyphene**	
HCL Salt	0.23
Napsylate	0.15
Sufentanil	2.5
Tapentadol	0.4
Tramadol	0.1

*Fentanyl conversion factor for micrograms (per hour).
**Propoxyphene conversion factor from the CDC and Thiels et al. (2019).
Sources: The Centers for Medicare and Medicaid Services (CMS), the Centers for Disease Control and Prevention (CDC), and Thiels et al. (2019).

Table A.3: The Effect of Excess Payments to MA Plans on MA-PDP Enrollment Across Years

	MA-PDP Enrollment	
	All Part D Enrollees	Part D with Any Opioid Use
	(1)	(2)
All Years	0.00362***	0.00354***
	(0.00059)	(0.00055)
	2,251,773	**698,382**
By Sample Year		
2008	0.00259***	0.00244***
	(0.000565)	(0.00054)
	191,265	**59,757**
2009	0.00301***	0.002780***
	(0.00064)	(0.000602)
	202,992	**63,746**
2010	0.00384***	0.00374***
	(0.00073)	(0.00069)
	215,693	**68,000**
2011	0.00412***	0.00416***
	(0.00066)	(0.00063)
	251,825	**78,541**
2012	0.00359***	0.00349***
	(0.00065)	(0.00061)
	248,902	**77,796**
2013	0.00394***	0.00388***
	(0.00058)	(0.00055)
	344,771	**108,648**
2014	0.00364***	0.00363***
	(0.00060)	(0.00056)
	374,104	**114,715**
2015	0.00343***	0.00341***
	(0.00057)	(0.00054)
	422,221	**127,719**

Notes: Estimates corresponds to α_1 from Equation 1.5. Standard errors are clustered at the county-level. *** denotes significance at the one-percent level; ** denotes significance at the five-percent level; * denotes significance at the ten-percent level.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table A.4: The Impact of MA-PDP Enrollment on Any Opioid Use Across the Sample Period (Part D Enrollees)

	Any Opioid Use			
	Mean	OLS Estimate	IV Estimate	Exog (p-value)
	(1)	(2)	(3)	(4)
All Years	0.3101	-0.0258***	-0.0262	0.9813
(N = 2,251,773)		(0.0018)	(0.0201)	
By Sample Year				
2008	0.3124	-0.0192***	-0.061	0.2504
(N = 191,265)		(0.0043)	(0.039)	
2009	0.3140	-0.0207***	0.008	0.3968
(N = 202,992)		(0.0038)	(0.033)	
2010	0.3153	-0.02846***	-0.022	0.7798
(N = 215,693)		(0.00301)	(0.023)	
2011	0.3119	-0.0277***	-0.012	0.4185
(N = 251,825)		(0.0024)	(0.019)	
2012	0.3126	-0.0255***	-0.031	0.8312
(N = 248,902)		(0.0029)	(0.024)	
2013	0.3151	-0.0263***	-0.041**	0.4858
(N = 344,771)		(0.0022)	(0.021)	
2014	0.3066	-0.0269***	-0.032	0.8076
(N = 374,104)		(0.0023)	(0.021)	
2015	0.3012	-0.0265***	-0.024	0.9198
(N = 422,221)		(0.0022)	(0.023)	

Notes: Column 1 contains outcome averages. Column 2 contains OLS estimates of β_1 from Equation 1.4. Column 3 contains 2SLS estimates of β_1 from Equation 1.6. Column 4 contains p-values from a robust test of exogeneity (Wooldridge 1995). Standard errors are clustered at the county-level. *** denotes significance at the one-percent level; ** denotes significance at the five-percent level; * denotes significance at the ten-percent level.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table A.5: The Impact of MA-PDP Enrollment on Intensity of Opioid Use Across the Sample Period (Part D Enrollees)

	ln(Annual Daily MED)				**ln(Max Daily MED)**				**Any Daily MED $\geq$ 50**			
	Mean[a] (1)	OLS Estimate (2)	IV Estimate (3)	Exog (p-value) (4)	Mean[a] (5)	OLS Estimate (6)	IV Estimate (7)	Exog (p-value) (8)	Mean (9)	OLS Estimate (10)	IV Estimate (11)	Exog (p-value) (12)
All Years	34.93	-0.0157***	-0.060	0.3389	44.29	-0.0289***	-0.049	0.6490	0.3124	-0.0154***	0.010	0.4439
(N = 698,382)		(0.0046)	(0.049)			(0.0049)	(0.048)			(0.0034)	(0.035)	
By Sample Year												
2008	41.56	0.012	-0.37**	0.0043	53.32	-0.0044	-0.35**	0.0082	0.4299	-0.0159*	-0.150**	0.0726
(N = 59,757)		(0.013)	(0.15)			(0.0138)	(0.14)			(0.0089)	(0.074)	
2009	41.53	-0.0445*	-0.278***	0.0131	53.03	-0.064***	-0.282***	0.0269	0.4279	-0.0435***	-0.127*	0.2225
(N = 63,746)		(0.0099)	(0.097)			(0.011)	(0.099)			(0.0078)	(0.067)	
2010	39.74	-0.0238***	-0.080	0.3730	50.85	-0.0378***	-0.077	0.5743	0.4009	-0.0271***	0.010	0.4347
(N = 68,000)		(0.0077)	(0.067)			(0.0084)	(0.073)			(0.0058)	(0.048)	
2011	33.19	-0.0055	-0.019	0.7612	42.36	-0.0212***	-0.007	0.7632	0.2694	-0.0039	0.019	0.4880
(N = 78,541)		(0.0064)	(0.048)			(0.0068)	(0.049)			(0.0049)	(0.036)	
2012	33.11	-0.0079	0.036	0.4123	42.07	-0.0161**	0.061	0.1370	0.2743	-0.0032	0.085*	0.0298
(N = 77,796)		(0.0069)	(0.056)			(0.0073)	(0.056)			(0.0052)	(0.044)	
2013	32.61	-0.0097	0.001	0.8217	41.23	-0.0233***	0.008	0.5109	0.2698	-0.0108***	0.036	0.1628
(N = 108,648)		(0.0061)	(0.049)			(0.0063)	(0.049)			(0.0041)	(0.036)	
2014	32.56	-0.0187***	-0.043	0.6152	41.05	-0.0317***	-0.023	0.8506	0.2795	-0.01596***	0.027	0.2415
(N = 114,715)		(0.0052)	(0.049)			(0.0057)	(0.049)			(0.00401)	(0.037)	
2015	32.25	-0.0218***	-0.025	0.9524	40.24	-0.0323***	-0.020	0.8300	0.2679	-0.0161***	0.031	0.2926
(N = 127,179)		(0.0051)	(0.056)			(0.0055)	(0.059)			(0.0039)	(0.047)	

Notes: Column 1 contains outcome averages. Column 2 contains OLS estimates of β_1 from Equation 1.4. Column 3 contains 2SLS estimates of β_1 from Equation 1.6. Column 4 contains p-values from a robust test of exogeneity (Wooldridge 1995). Standard errors are clustered at the county-level. *** denotes significance at the one-percent level; ** denotes significance at the five-percent level; * denotes significance at the ten-percent level.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table A.6: The Effect of MA-PDP Enrollment on Any Opioid Use (Sensitivity Analysis)

	Any Opioid Use				
	(1)	(2)	(3)	(4)	(5)
All Years	-0.067**	-0.057***	-0.054**	-0.0258	-0.0262
(N = 2,251,773)	(0.033)	(0.022)	(0.022)	(0.202)	(0.201)
By Sample Year					
2008	-0.104*	-0.100**	-0.099**	-0.054	-0.061
(N = 191,265)	(0.062)	(0.045)	(0.046)	(0.036)	(0.039)
2009	-0.028	-0.022	-0.020	0.006	0.008
(N = 202,992)	(0.048)	(0.034)	(0.034)	(0.033)	(0.033)
2010	-0.059*	-0.048**	-0.044*	-0.020	-0.022
(N = 215,693)	(0.035)	(0.024)	(0.025)	(0.023)	(0.023)
2011	-0.047	-0.041	-0.038	-0.011	-0.012
(N = 251,825)	(0.033)	(0.021)	(0.021)	(0.019)	(0.019)
2012	-0.068**	-0.061***	-0.056**	-0.030	-0.031
(N = 248,902)	(0.033)	(0.022)	(0.023)	(0.024)	(0.024)
2013	-0.077**	-0.064***	-0.061***	-0.035	-0.041**
(N = 344,771)	(0.033)	(0.023)	(0.023)	(0.021)	(0.021)
2014	-0.0775**	-0.066***	-0.064***	-0.034	-0.032
(N = 374,104)	(0.0304)	(0.022)	(0.022)	(0.022)	(0.021)
2015	-0.067	-0.054	-0.052	-0.025	-0.024
(N = 422,221)	(0.034)	(0.024)	(0.024)	(0.023)	(0.023)
Census Region and Year FEs		X	X	X	X
Individual Characteristics			X	X	X
County Characteristics				X	X
State Characteristics					X

Notes: Table contains IV estimates of β_1 from Equation 1.6. Standard errors are clustered at the county-level. *** denotes significance at the one-percent level; ** denotes significance at the five-percent level; * denotes significance at the ten-percent level.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table A.7: The Effect of MA-PDP Enrollment on Annual Daily MED Use (Sensitivity Analysis)

	ln(Annual Daily MED)				
	(1)	(2)	(3)	(4)	(5)
All Years	-0.013	0.010	-0.024	-0.060	-0.060
(N = 698,382)	(0.062)	(0.055)	(0.053)	(0.048)	(0.049)
By Sample Year					
2008	-0.37*	-0.37**	-0.39**	-0.35**	-0.37**
(N = 59,757)	(0.19)	(0.19)	(0.19)	(0.14)	(0.15)
2009	-0.32***	-0.32***	-0.35***	-0.279***	-0.278***
(N = 63,746)	(0.12)	(0.12)	(0.12)	(0.098)	(0.097)
2010	-0.031	-0.028	-0.057	-0.069	-0.080
(N = 68,000)	(0.076)	(0.078)	(0.077)	(0.068)	(0.067)
2011	0.053	0.065	0.024	-0.021	-0.019
(N = 78,541)	(0.069)	(0.055)	(0.053)	(0.049)	(0.048)
2012	0.113	0.123*	0.071	0.034	0.036
(N = 77,796)	(0.079)	(0.066)	(0.062)	(0.058)	(0.056)
2013	0.053	0.062	0.030	0.0056	0.001
(N = 108,648)	(0.061)	(0.054)	(0.052)	(0.0503)	(0.049)
2014	0.021	0.032	0.004	-0.044	-0.043
(N = 114,715)	(0.063)	(0.052)	(0.049)	(0.049)	(0.049)
2015	0.068	0.073	0.038	-0.025	-0.025
(N = 127,179)	(0.063)	(0.055)	(0.051)	(0.056)	(0.056)
Census Region and Year FEs		X	X	X	X
Individual Characteristics			X	X	X
County Characteristics				X	X
State Characteristics					X

Notes: Table contains IV estimates of β_1 from Equation 1.6. Standard errors are clustered at the county-level. *** denotes significance at the one-percent level; ** denotes significance at the five-percent level; * denotes significance at the ten-percent level.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table A.8: The Effect of MA-PDP Enrollment on Maximum Daily MED Use (Sensitivity Analysis)

	ln(Max Daily MED)				
	(1)	(2)	(3)	(4)	(5)
All Years	-0.017	0.014	-0.018	-0.051	-0.049
(N = 698,382)	(0.062)	(0.056)	(0.053)	(0.048)	(0.048)
By Sample Year					
2008	-0.34**	-0.34**	-0.36**	-0.33**	-0.35**
(N = 59,757)	(0.17)	(0.17)	(0.17)	(0.13)	(0.14)
2009	-0.30***	-0.30***	-0.33***	-0.283***	-0.282***
(N = 63,746)	(0.11)	(0.11)	(0.11)	(0.098)	(0.098)
2010	-0.0531	-0.045	-0.069	-0.068	-0.077
(N = 68,000)	(0.0801)	(0.084)	(0.083)	(0.073)	(0.073)
2011	0.063	0.079	0.039	-0.012	-0.007
(N = 78,541)	(0.074)	(0.059)	(0.057)	(0.0502)	(0.049)
2012	0.121	0.136	0.085	0.058	0.061
(N = 77,796)	(0.082)	(0.067)	(0.063)	(0.058)	(0.056)
2013	0.046	0.061	0.028	0.012	0.008
(N = 108,648)	(0.061)	(0.053)	(0.051)	(0.051)	(0.049)
2014	0.017	0.036	0.008	-0.026	-0.023
(N = 114,715)	(0.063)	(0.053)	(0.050)	(0.049)	(0.049)
2015	0.058	0.069	0.034	-0.020	-0.020
(N = 127,179)	(0.066)	(0.057)	(0.052)	(0.059)	(0.059)
Census Region and Year FEs		X	X	X	X
Individual Characteristics			X	X	X
County Characteristics				X	X
State Characteristics					X

Notes: Table contains IV estimates of β_1 from Equation 1.6. Standard errors are clustered at the county-level. *** denotes significance at the one-percent level; ** denotes significance at the five-percent level; * denotes significance at the ten-percent level.
Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

Table A.9: The Effect of MA-PDP Enrollment on Any Daily MED $\geq$ 50 (Sensitivity Analysis)

	Any Daily MED $\geq$ 50				
	(1)	(2)	(3)	(4)	(5)
All Years	0.016	0.038	0.022	0.009	0.103
(N = 698,382)	(0.043)	(0.039)	(0.037)	(0.035)	(0.0352)
By Sample Year					
2008	-0.172*	-0.174*	-0.180**	-0.150**	-0.150**
(N = 59,757)	(0.089)	(0.091)	(0.091)	(0.068)	(0.074)
2009	-0.174**	-0.173**	-0.184**	-0.127*	-0.127*
(N = 63,746)	(0.073)	(0.074)	(0.074)	(0.067)	(0.067)
2010	-0.005	0.003	-0.008	0.017	0.010
(N = 68,000)	(0.047)	(0.051)	(0.051)	(0.049)	(0.048)
2011	0.041	0.052	0.033	0.016	0.019
(N = 78,541)	(0.052)	(0.043)	(0.043)	(0.038)	(0.036)
2012	0.105*	0.118**	0.092**	0.083*	0.085*
(N = 77,796)	(0.056)	(0.046)	(0.045)	(0.046)	(0.044)
2013	0.049	0.058	0.041	0.036	0.036
(N = 108,648)	(0.044)	(0.037)	(0.036)	(0.037)	(0.036)
2014	0.043	0.055	0.039	0.026	0.027
(N = 114,715)	(0.046)	(0.037)	(0.036)	(0.037)	(0.037)
2015	0.086*	0.091**	0.073*	0.032	0.031
(N = 127,179)	(0.051)	(0.044)	(0.041)	(0.047)	(0.047)
Census Region and Year FEs		X	X	X	X
Individual Characteristics			X	X	X
County Characteristics				X	X
State Characteristics					X

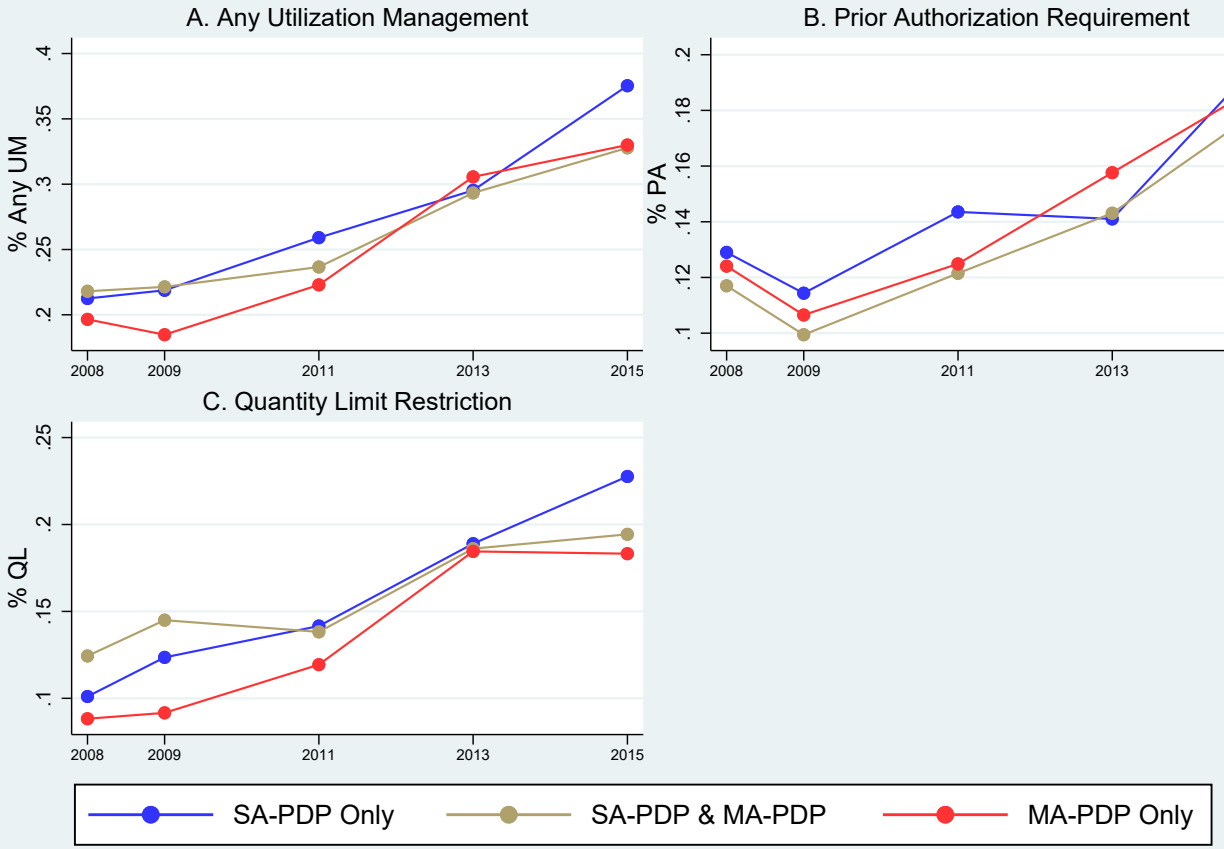
Notes: Table contains IV estimates of β_1 from Equation 1.6. Standard errors are clustered at the county-level. *** denotes significance at the one-percent level; ** denotes significance at the five-percent level; * denotes significance at the ten-percent level. Source: 2008-2015 20 Percent Sample of Medicare Beneficiaries.

APPENDIX B

Appendix to Insurer Incentives and Benefit Design for Opioids

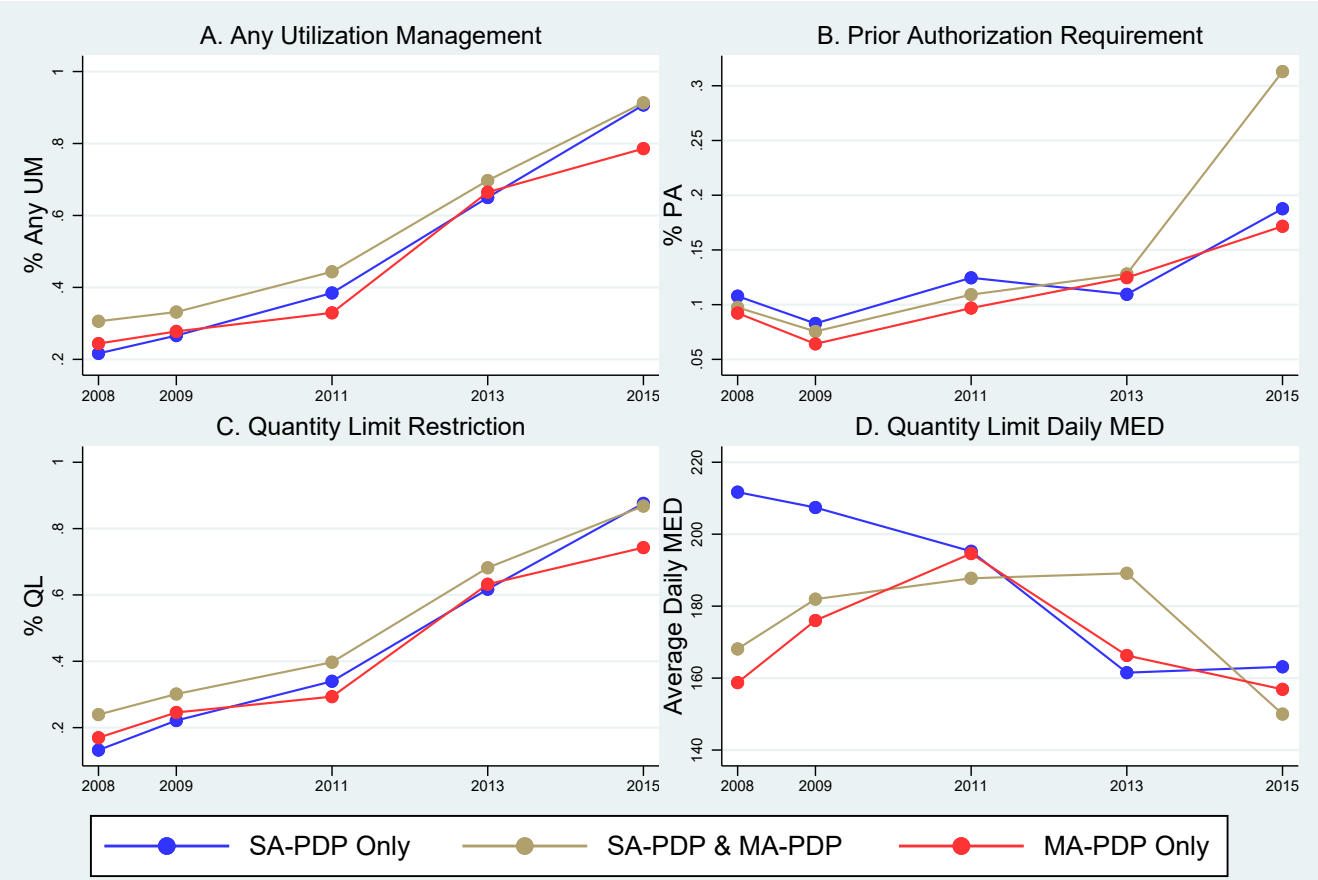
B.1 Supplemental Figures

Figure B.1: Utilization Management Rules Over Time (All Drugs)



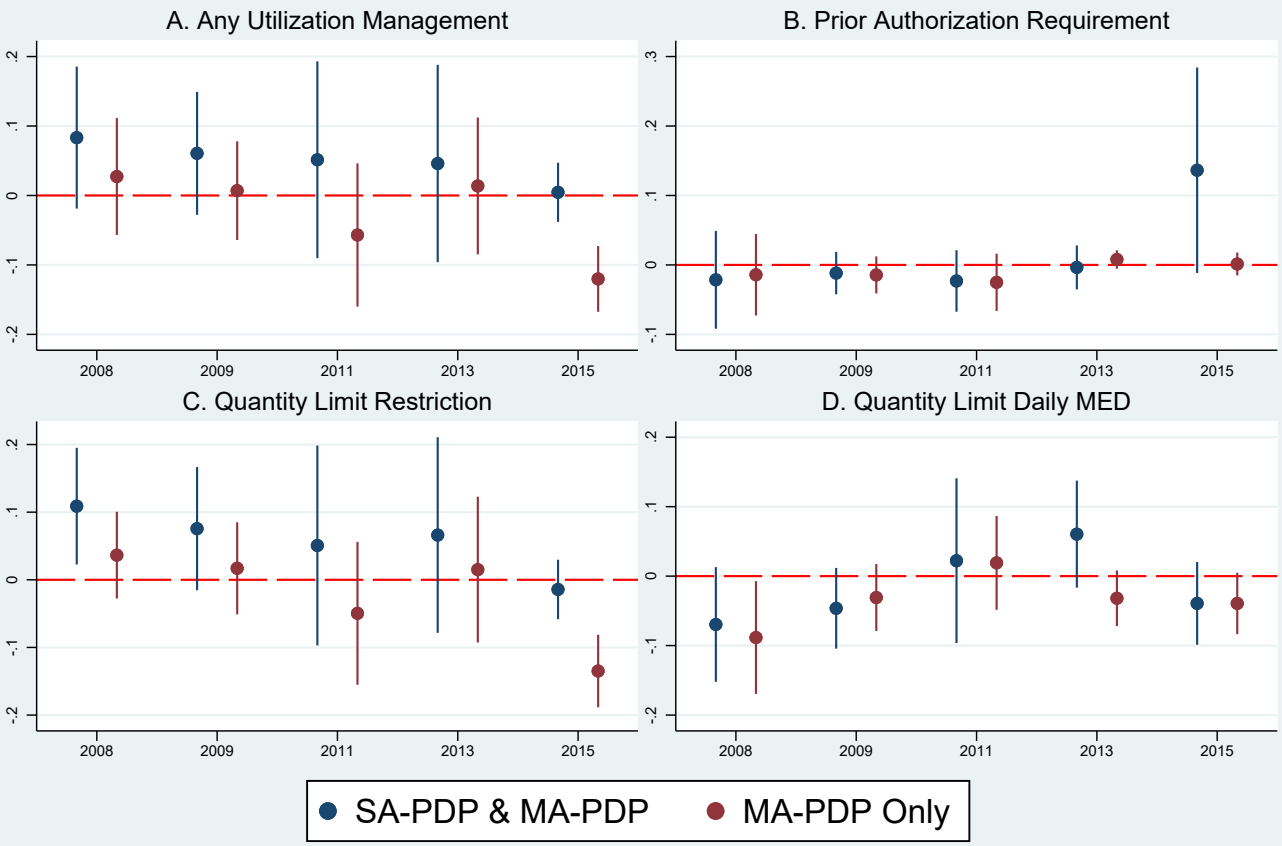
Note: Figure presents outcome means over time, stratified by formulary type.
Source: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files.

Figure B.2: Utilization Management Rules Over Time (Opioids)



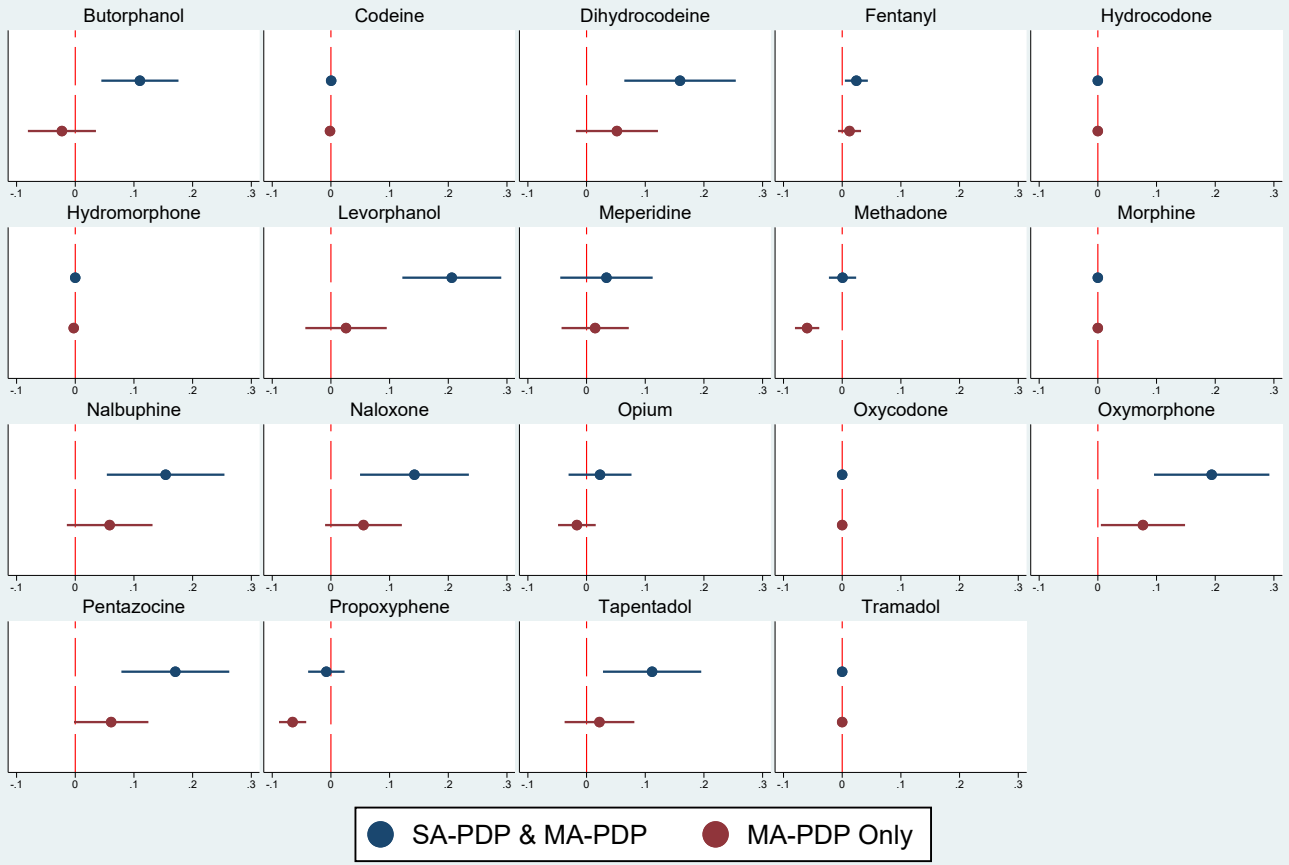
Notes: Figure presents outcome means over time, stratified by formulary type. Panel D. is conditional on a quantity limit restriction.
Source: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files.

Figure B.3: Differences in Utilization Management Rules Over Time (NDC FEs)



Notes: Figure presents estimates of β_1(SA-PDP & MA-PDP) and β_2(MA-PDP Only) from Equation 2.1 (and 95% CIs), stratified by sample year. Panel D. is conditional on a quantity limit restriction.
Source: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files.

Figure B.4: Ingredient Estimates



The figure contains estimates of θ_1(SA-PDP & MA-PDP) and θ_2(MA-PDP Only) from Equation 2.3 (and 95% CIs).
Sources: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files.

B.2 Supplemental Tables

Table B.1: Analysis of Utilization Management Rules Across All Drugs

	Any UM		**Prior Authorization**		**Quantity Limit**	
	(1)	(2)	(3)	(4)	(5)	(6)
SA-PDP & MA-PDP	-0.012	-0.013	-0.0131*	-0.0137*	0.0021	0.0017
	(0.012)	(0.013)	(0.0076)	(0.0076)	(0.0104)	(0.0105)
SA-PDP & MA-PDP X Opioid	0.074***	0.069***	0.024*	0.017	0.068***	0.066***
	(0.022)	(0.022)	(0.014)	(0.013)	(0.023)	(0.023)
MA-PDP Only	-0.024***	-0.025***	-0.0037	-0.0052	-0.0239***	-0.0274***
	(0.0080)	(0.0080)	(0.0054)	(0.0054)	(0.0069)	(0.0069)
MA-PDP Only X Opioid	0.008	0.011	-0.0091	-0.0046	0.013	0.014
	(0.016)	(0.016)	(0.0060)	(0.0053)	(0.017)	(0.017)
Outcome Mean	0.2564	0.2564	0.1413	0.1413	0.1431	0.1431
Year x Opioid FEs	X		X		X	
Year x NDC FEs		X		X		X
Observations	4,093,765	4,093,765	4,093,765	4,093,765	4,093,765	4,093,765

Notes: The table reports estimates of δ_1(SA-PDP & MA-PDP), δ_2(MA-PDP Only), δ_3(SA-PDP & MA-PDP X Opioid), and δ_4(MA-PDP Only X Opioid) from Equation 2.2. The sample includes all drugs that appear throughout the data years. Columns 1 and 2 present estimates from models in which any utilization management (UM) rule is the outcome; Columns 3 and 4 present estimates from models in which the outcome is a prior authoization requirement; and, columns 5 and 6 present estimates from models in which the outcome is a quantity limit restriction. Columns 1, 3, and 5 include year fixed effects fully interacted with an indicator for opioid drugs; and, columns 2, 4, and 6 include year by NDC effects. Standard errors are clustered at the formulary level. *p< 0.10, ** p< 0.05, *** p< 0.01.
Source: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files.

Table B.2: Parent Organization Analysis

	Any UM			Prior Authorization			Quantity Limit			ln(Daily MED)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Main Results Replication												
SA-PDP & MA-PDP	0.041	0.037	0.037	0.014	0.013	0.007	0.045*	0.042*	0.043*	-0.036	-0.024	-0.0069
	(0.026)	(0.026)	(0.027)	(0.018)	(0.018)	(0.017)	(0.025)	(0.025)	(0.025)	(0.033)	(0.024)	(0.0204)
MA-PDP Only	-0.015	-0.015	-0.016	-0.0124	-0.0099	-0.0098	-0.009	-0.010	-0.012	-0.059***	-0.042***	-0.033***
	(0.019)	(0.019)	(0.019)	(0.0093)	(0.0089)	(0.0088)	(0.019)	(0.019)	(0.019)	(0.022)	(0.014)	(0.012)
Outcome Mean*	0.4623	0.4623	0.4623	0.1145	0.1145	0.1145	0.4161	0.4161	0.4161	169.77	169.77	169.77
Year FEs	X			X			X			X		
Year x Ing FEs		X			X			X			X	
Year x NDC FEs			X			X			X			X
B. Parent Organization Controls												
SA-PDP & MA-PDP	0.026	0.025	0.019	-0.012	-0.011	-0.019	0.042**	0.040**	0.041	-0.041	0.005	0.007
	(0.018)	(0.018)	(0.026)	(0.017)	(0.017)	(0.023)	(0.019)	(0.019)	(0.031)	(0.026)	(0.013)	(0.011)
MA-PDP Only	0.019	0.014	0.007	0.0149	0.0126	-0.005	0.015	0.009	0.010	-0.023	-0.0117	-0.0057
	(0.017)	(0.017)	(0.024)	(0.0102)	(0.0099)	(0.012)	(0.017)	(0.017)	(0.027)	(0.015)	(0.0071)	(0.0076)
Outcome Mean*	0.4623	0.4623	0.4623	0.1145	0.1145	0.1145	0.4161	0.4161	0.4161	169.77	169.77	169.77
Year x Par Org FEs	X			X			X			X		
Year x Par Org x Ing FEs		X			X			X			X	
Year x Par Org x NDC FEs			X			X			X			X
Observations	165,535	165,535	165,535	165,535	165,535	165,535	165,535	165,535	165,535	68,882	68,882	68,882

Notes: The table reports estimates of β_1 (SA-PDP & MA-PDP) and β_2 (MA-PDP Only) from Equation 2.1. The analysis is limited to Part D formularies that are unique to one parent organization. Panel A. replicates the main results from Table 2.2 on the limited sample. Panel B. includes an additional layer of parent organization controls. Columns 1, 2, and 3 present estimates from models in which any utilization management (UM) rule is the outcome; Columns 4, 5, and 6 present estimates from models in which the outcome is a prior authoization requirement; columns 7, 8, and 9 present estimates from models in which the outcome is a quantity limit restriction; and, columns 10, 11, and 12 present estimates from models in which the outcome is the natural logarithm of the maximum daily morphine equivalent dosage (MED) allowance, conditional on a quantity limit restriction. Columns 1, 4, 7, and 10 include year (by parent organization effects); columns 2, 5, 8, and 11 include year (by parent organization) by ingredient effects (ex..."oxycodone X 2011"); and, columns 3, 6, 9, and 12 include year (by parent organization) by NDC effects. Standard errors are clustered at the formulary level.
*p< 0.10, ** p< 0.05, *** p< 0.01.
*The means corresponding to Daily MED are not log-transformed.
Source: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files.

Table B.3: Analysis of Opioid Utilization Management Rules Across Sample Years

	Any UM			**Prior Authorization**			**Quantity Limit**			**ln(Daily MED)**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
2008												
SA-PDP & MA-PDP	0.089*	0.085*	0.083	-0.010	-0.013	-0.021	0.107**	0.104**	0.109**	-0.27**	-0.129**	-0.069*
	(0.051)	(0.051)	(0.052)	(0.036)	(0.036)	(0.036)	(0.044)	(0.044)	(0.044)	(0.11)	(0.062)	(0.042)
MA-PDP Only	0.027	0.026	0.027	-0.0155	-0.0145	-0.014	0.037	0.035	0.036	-0.302***	-0.135**	-0.088**
	(0.042)	(0.042)	(0.043)	(0.0303)	(0.0301)	(0.029)	(0.032)	(0.033)	(0.033)	(0.102)	(0.055)	(0.041)
Outcome Mean*	0.2516	0.2516	0.2516	0.0969	0.0969	0.0969	0.1769	0.1769	0.1769	170.42	170.42	170.42
Observations	38,890	38,890	38,890	38,890	38,890	38,890	38,890	38,890	38,890	6,880	6,880	6,880
2009												
SA-PDP & MA-PDP	0.065	0.061	0.061	-0.007	-0.009	-0.012	0.079*	0.075	0.076	-0.149*	-0.066*	-0.046
	(0.044)	(0.045)	(0.045)	(0.016)	(0.015)	(0.016)	(0.046)	(0.046)	(0.046)	(0.085)	(0.035)	(0.029)
MA-PDP Only	0.012	0.009	0.007	-0.019	-0.018	-0.014	0.024	0.022	0.017	-0.145	-0.040	-0.031
	(0.036)	(0.036)	(0.036)	(0.014)	(0.013)	(0.014)	(0.035)	(0.035)	(0.035)	(0.072)	(0.029)	(0.024)
Outcome Mean*	0.2834	0.2834	0.2834	0.0706	0.0706	0.0706	0.2486	0.2486	0.2486	184.11	184.11	184.11
Observations	37,389	37,389	37,389	37,389	37,389	37,389	37,389	37,389	37,389	9,296	9,296	9,296
2011												
SA-PDP & MA-PDP	0.059	0.056	0.051	-0.015	-0.018	-0.023	0.057	0.054	0.051	-0.078	0.011	0.0222
	(0.071)	(0.071)	(0.072)	(0.024)	(0.022)	(0.022)	(0.074)	(0.074)	(0.075)	(0.097)	(0.062)	(0.0601)
MA-PDP Only	-0.055	-0.053	-0.057	-0.028	-0.025	-0.025	-0.046	-0.046	-0.049	0.022	0.011	0.019
	(0.051)	(0.052)	(0.052)	(0.023)	(0.021)	(0.021)	(0.052)	(0.053)	(0.054)	(0.084)	(0.038)	(0.034)
Outcome Mean*	0.3591	0.3591	0.3591	0.1037	0.1037	0.1037	0.3198	0.3198	0.3198	193.21	193.21	193.21
Observations	29,006	29,006	29,006	29,006	29,006	29,006	29,006	29,006	29,006	9,275	9,275	9,275
Ingredient FEs		X			X			X			X	
NDC FEs			X			X			X			X

Table B.3, Continued

	Any UM			Prior Authorization			Quantity Limit			ln(Daily MED)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
2013												
SA-PDP & MA-PDP	0.047	0.041	0.046	0.019	0.0019	-0.004	0.065	0.061	0.066	0.1429***	0.058	0.061
	(0.071)	(0.072)	(0.072)	(0.019)	(0.015)	(0.016)	(0.072)	(0.074)	(0.073)	(0.046)	(0.049)	(0.039)
MA-PDP Only	0.015	0.012	0.014	0.0153	0.0103	0.0078	0.015	0.013	0.015	0.017	-0.032	-0.0318
	(0.049)	(0.049)	(0.049)	(0.0098)	(0.0077)	(0.0067)	(0.054)	(0.055)	(0.055)	(0.029)	(0.025)	(0.0203)
Outcome Mean*	0.6643	0.6643	0.6643	0.1218	0.1218	0.1218	0.6332	0.6332	0.6332	167.303	167.303	167.303
Observations	33,878	33,878	33,878	33,878	33,878	33,878	33,878	33,878	33,878	21,452	21,452	21,452
2015												
SA-PDP & MA-PDP	0.006	0.008	0.005	0.1253	0.145*	0.136*	-0.008	-0.0103	-0.014	-0.088**	-0.046	-0.0392
	(0.022)	(0.021)	(0.022)	(0.0806)	(0.079)	(0.075)	(0.024)	(0.023)	(0.022)	(0.043)	(0.032)	(0.0303)
MA-PDP Only	-0.121***	-0.117***	-0.1201***	-0.016	0.0015	0.0013	-0.133***	-0.129***	-0.135***	-0.0579*	-0.045*	-0.039*
	(0.026)	(0.025)	(0.024)	(0.014)	(0.0094)	(0.0084)	(0.029)	(0.028)	(0.027)	(0.0303)	(0.023)	(0.022)
Outcome Mean*	0.8175	0.8175	0.8175	0.1870	0.1870	0.1870	0.7762	0.7762	0.7762	167.303	167.303	167.303
Observations	31,382	31,382	31,382	31,382	31,382	31,382	31,382	31,382	31,382	24,360	24,360	24,360
Ingredient FEs		X			X			X			X	
NDC FEs			X			X			X			X

Notes: The table reports estimates of β_1 (SA-PDP & MA-PDP) and β_2 (MA-PDP Only) from Equation 2.1, stratified by sample years. The sample includes prescription opioids that appear throughout the data years. Columns 1, 2, and 3 present estimates from models in which any utilization management (UM) rule is the outcome; Columns 4, 5, and 6 present estimates from models in which the outcome is a prior authoization requirement; columns 7, 8, and 9 present estimates from models in which the outcome is a quantity limit restriction; and, columns 10, 11, and 12 present estimates from models in which the outcome is the natural logarithm of the maximum daily morphine equivalent dosage (MED) allowance, conditional on a quantity limit restriction. Columns 1, 4, 7, and 10 include year fixed effects; columns 2, 5, 8, and 11 include ingredient by year effects (ex..."oxycodone X 2011"); and, columns 3, 6, 9, and 12 include year by NDC effects. Standard errors are clustered at the formulary level. *p< 0.10, ** p< 0.05, *** p< 0.01.

*The means corresponding to Daily MED are not log-transformed.

Source: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files.

Table B.4: Analysis of Ingredient Coverage

	Ingredient Covered	
	(1)	(2)
Butorphanol		
SA-PDP & MA-PDP	0.110***	0.028
	(0.033)	(0.042)
MA-PDP Only	-0.023	0.019
	(0.029)	(0.037)
Outcome Mean	0.8244	0.9176
Observations	1,105	1,105
Codeine		
SA-PDP & MA-PDP	0.00045	0.000026
	(0.00050)	(0.0000031)
MA-PDP Only	-0.0015	-0.000089
	(0.0015)	(0.000091)
Outcome Mean	0.9991	0.9999
Observations	1,105	1,105
Dihydrocodeine		
SA-PDP & MA-PDP	0.159***	0.194**
	(0.048)	(0.088)
MA-PDP Only	0.052	0.078
	(0.036)	(0.098)
Outcome Mean	0.5466	0.6279
Observations	1,105	1,105
Fentanyl		
SA-PDP & MA-PDP	0.241**	0.0033
	(0.0099)	(0.0023)
MA-PDP Only	0.0125	0.0014
	(0.0099)	(0.018)
Outcome Mean	0.9900	0.9984
Observations	1,105	1,105
Hydrocodone		
SA-PDP & MA-PDP	–	–
MA-PDP Only	–	–
Outcome Mean	1	1
Observations	1,105	1,105
Unweighted	X	
Enrollment Weighted		X

Table B.4, Continued

	Ingredient Covered	
	(1)	(2)
Hydromorphone		
SA-PDP & MA-PDP	0.00005	0.0000019
	(0.00061)	(0.000051)
MA-PDP Only	-0.0026	-0.000061
	(0.0018)	((0.000045)
Outcome Mean	0.9982	0.9999
Observations	1,105	1,105
Levorphanol		
SA-PDP & MA-PDP	0.206***	0.233***
	(0.043)	(0.079)
MA-PDP Only	0.026	0.093
	(0.035)	(0.083)
Outcome Mean	0.7059	0.7642
Observations	1,105	1,105
Meperidine		
SA-PDP & MA-PDP	0.0339	0.039
	(0.0401)	(0.056)
MA-PDP Only	0.015	0.107**
	(0.029)	(0.053)
Outcome Mean	0.5385	0.5222
Observations	1,105	1,105
Methadone		
SA-PDP & MA-PDP	0.0006	0.0039
	(0.012)	(0.028)
MA-PDP Only	-0.059***	-0.0103**
	(0.011)	(0.0041)
Outcome Mean	0.9602	0.9964
Observations	1,105	1,105
Morphine		
SA-PDP & MA-PDP	–	–
MA-PDP Only	–	–
Outcome Mean	1	1
Observations	1,105	1,105
Nalbuphine		
SA-PDP & MA-PDP	0.154***	0.202**
	(0.051)	(0.080)
MA-PDP Only	0.059	0.119
	(0.037)	(0.081)
Outcome Mean	0.5946	0.7467
Observations	1,105	1,105
Unweighted	X	
Enrollment Weighted		X

Table B.4, Continued

	Ingredient Covered (1)	(2)
Naloxone		
SA-PDP & MA-PDP	0.1424***	0.132*
	(0.047)	(0.072)
MA-PDP Only	0.056*	0.098
	(0.033)	((0.061)
Outcome Mean	0.4262	0.4571
Observations	1,105	1,105
Opium (2008)		
SA-PDP & MA-PDP	0.065	0.25
	(0.107)	(0.21)
MA-PDP Only	-0.089	-0.15
	(0.085)	(0.24)
Outcome Mean	0.4076	0.6185
Observations	211	211
Oxycodone		
SA-PDP & MA-PDP	–	–
MA-PDP Only	–	–
Outcome Mean	1	1
Observations	1,105	1,105
Oxymorphone		
SA-PDP & MA-PDP	0.1939***	0.101
	(0.0501)	(0.106)
MA-PDP Only	0.077**	0.136*
	(0.037)	(0.077)
Outcome Mean	0.6154	0.7294
Observations	1,105	1,105
Pentazocine		
SA-PDP & MA-PDP	0.171***	0.195**
	(0.047)	(0.079)
MA-PDP Only	0.061*	0.123*
	(0.032)	(0.063)
Outcome Mean	0.4109	0.4411
Observations	1,105	1,105
Propoxyphene (< 2011)		
SA-PDP & MA-PDP	-0.032	-0.0026
	(0.030)	(0.0094)
MA-PDP Only	-0.158***	-0.1764**
	(0.027)	(0.087)
Outcome Mean	0.8801	0.9642
Observations	442	442
Unweighted	X	
Enrollment Weighted		X

Table B.4, Continued

	Ingredient Covered	
	(1)	(2)
Tapentadol (> 2008)		
SA-PDP & MA-PDP	0.1521***	0.014
	(0.057)	(0.12)
MA-PDP Only	0.028	0.02
	(0.037)	(0.0.11)
Outcome Mean	0.3546	0.3693
Observations	894	894
Tramadol		
SA-PDP & MA-PDP	–	–
MA-PDP Only	–	–
Outcome Mean	1	1
Observations	1,105	1,105
Unweighted	X	
Enrollment Weighted		X

Notes: The table reports estimates of θ_1(SA-PDP & MA-PDP) and θ_2(MA-PDP Only) from Equation 2.3. The unit of observation is the formulary-year. Estimates in column 1 are unweighted, while estimates in column 2 are weighted by the number of Medicare enrollees within Part D plans that correspond to formularies. Opium products appear on Part D formularies only during 2008; propoxyphene products appear on Part D formularies prior to 2011 (2008 and 2009); tapentadol products appear on Part D formularies after 2008 (2009, 2011, 2013, and 2015). Robust standard errors are included in parentheses. *p< 0.10, ** p< 0.05, *** p< 0.01.
Sources: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files, and CMS Plan Enrollment Files.

Table B.5: Analysis of Propoxyphene Drugs and Non-Propoxyphene Opioids (2008 & 2009)

	Any UM			Prior Authorization			Quantity Limit			ln(Daily MED)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
A. Propoxyphene Drugs												
SA-PDP & MA-PDP	0.028	–	0.035	-0.049	–	-0.058	0.078	–	0.094*	-0.022	–	-0.115***
	(0.051)		(0.051)	(0.037)		(0.034)	(0.041)		(0.039)	(0.036)		(0.041)
MA-PDP Only	0.012	–	0.015	-0.072*	–	-0.077**	0.088**	–	0.096**	-0.033	–	-0.089**
	(0.051)		(0.051)	(0.037)		(0.034)	(0.041)		(0.039)	(0.036)		(0.037)
Outcome Mean*	0.2619	0.2619	0.2619	0.0540	0.0540	0.0540	0.2100	0.2100	0.2100	140.52	140.52	140.52
Observations	2,757	2,757	2,757	2,757	2,757	2,757	2,757	2,757	2,757	579	579	579
B. Non-Propoxyphene Opioids												
Opioids												
SA-PDP & MA-PDP	0.080**	0.076**	0.074**	-0.008	-0.010	-0.016	0.095***	0.091***	0.093***	-0.201***	-0.090**	-0.049*
	(0.034)	(0.034)	(0.035)	(0.021)	(0.021)	(0.021)	(0.031)	(0.032)	(0.032)	(0.069)	(0.035)	(0.026)
MA-PDP Only	0.019	0.018	0.017	-0.015	-0.014	-0.012	0.028	0.026	0.024	-0.2105***	-0.077***	-0.051**
	(0.027)	(0.027)	(0.028)	(0.016)	(0.016)	(0.016)	(0.023)	(0.023)	(0.023)	(0.0606)	(0.028)	(0.022)
Outcome Mean*	0.2674	0.2674	0.2674	0.0852	0.0852	0.0852	0.2121	0.2121	0.2121	179.69	179.69	179.69
Observations	73,522	73,522	73,522	73,522	73,522	73,522	73,522	73,522	73,522	15,597	15,597	15,597
Year FEs	X			X			X			X		
Year x Ing FEs		X			X			X			X	
Year x NDC FEs			X			X			X			X

Notes: The table reports estimates of β_1 (SA-PDP & MA-PDP) and β_2 (MA-PDP Only) from Equation 2.1. The sample includes prescription opioids that appear on Part D formularies during 2008 and 2009. Panel A corresponds to the sample of propoxyphene NDCs that appear during these data years, while panel B corresponds to the sample of non-propoxyphene opioids during these years. Columns 1, 2, and 3 present estimates from models in which any utilization management (UM) rule is the outcome; Columns 4, 5, and 6 present estimates from models in which the outcome is a prior authoization requirement; columns 7, 8, and 9 present estimates from models in which the outcome is a quantity limit restriction; and, columns 10, 11, and 12 present estimates from models in which the outcome is the natural logarithm of the maximum daily morphine equivalent dosage (MED) allowance, conditional on a quantity limit restriction. Columns 1, 4, 7, and 10 include year fixed effects; columns 2, 5, 8, and 11 include ingredient by year effects (ex..."oxycodone X 2011"); and, columns 3, 6, 9, and 12 include year by NDC effects. Standard errors are clustered at the formulary level. *p< 0.10, ** p< 0.05, *** p< 0.01.
*The means corresponding to Daily MED are not log-transformed.
Source: CMS Prescription Drug Plan Formulary, Pharmacy Network, and Pricing Information Files.

APPENDIX C

Appendix to Changes in the Utilization of Mental Health Care Services and Mental Health at the Onset of Medicare

C.1 Supplemental Tables

Table C.1: Age 64 Means and Estimated Discontinuities for Alternative Outcomes, NHIS 2006-2013

Outcome:	Employed		Kessler K6 $\geq$ 13 (Serious Mental Illness)	
	Age 64 Mean (1)	RD Estimate (2)	Age 64 Mean (3)	RD Estimate (4)
Overall (Adults Aged 55-74) (N = 55,586)	40.59	1.22 (1.47)	2.91	0.87* (0.53)
Level of Education				
High School Dropout (N = 9,760)	26.27	-3.84 (3.25)	7.09	1.39 (2.03)
High School Graduate (N = 15,703)	36.67	3.19 (2.84)	3.14	0.75 (1.05)
At Least Some College (N = 30,123)	46.08	1.76 (2.03)	1.74	0.73 (0.50)

Notes: Odd-numbered columns contain the sample-weighted average among 64-year-olds. Even-numbered columns contain estimates of β_3 from Equation 3.1. Linearized standard errors appear in parentheses below the estimates. All models are fit to data years 2006-2013 of the NHIS Sample Adult and Person File data. ***Statistically significant at the 1 percent level; **Statistically significant at the 5 percent level; *Statistically significant at the 10 percent level.

Table C.2: Estimated Mental Health Discontinuities Across Age Windows and Models, NHIS 2006-2013

Outcome:	Did Not Get Mental Health Care Last Year (Costs)		Mental Health Visit Last Year		Kessler K6 [0-24]	
	RD Estimate		RD Estimate		RD Estimate	
	10 Year Window (55-74) (1)	3 Year Window (62-67) (2)	10 Year Window (55-74) (3)	3 Year Window (62-67) (4)	10 Year Window (55-74) (5)	3 Year Window (62-67) (6)
Overall	-0.98***	-1.02**	0.29	-0.83	0.09	0.28
	(0.34)	(0.41)	(0.77)	(0.88)	(0.12)	(0.60)
N	55,586	17,154	55,586	17,154	55,586	17,154
Level of Education						
High School Dropout	-2.37**	-1.64	0.99	1.51	0.09	0.29
	(1.09)	(1.26)	(1.47)	(1.81)	(0.39)	(2.38)
N	9,760	2,967	9,760	2,967	9,760	2,967
High School Graduate	-0.88	-1.79**	1.09	-1.34	0.11	0.97
	(0.63)	(0.73)	(1.28)	(1.58)	(0.24)	(1.14)
N	15,703	4,782	15,703	4,782	15,703	4,782
At Least Some College	-0.70*	-0.47	-0.25	-1.12	0.09	-0.06
	(0.39)	(0.51)	(1.17)	(1.36)	(0.13)	(0.58)
N	30,123	9,405	30,123	9,405	30,123	9,405
Specification	Quadratic	Linear	Quadratic	Linear	Quadratic	Linear

Notes: Columns (1), (3), and (5) contain estimates of β_3 from Equation 3.1; these estimates correspond with the discontinuity estimates presented in Table 3. Columns (2), (4), and (6) come from a local linear model estimated on the sample of 62-67-year-olds. Linearized standard errors appear below the estimates. Sample sizes appear below the standard errors. All models are fit to data years 2006-2013 of the NHIS Sample Adult and Person File data. ***Statistically significant at the 1 percent level; **Statistically significant at the 5 percent level; *Statistically significant at the 10 percent level.

Table C.3: Probit Regression of Under-65 Population with Any Insurance Coverage, NHIS 2006-2013

Outcome:	Any Insurance
Female	-0.00537
	(0.0233)
White	0.154***
	(0.0536)
Black	-0.0227
	(0.0600)
Hispanic	-0.414***
	(0.0376)
High School Graduate	0.322***
	(0.0311)
At Least Some College	0.624***
	(0.0305)
Midwest	-0.163***
	(0.0418)
South	-0.303***
	(0.0360)
West	-0.307***
	(0.0407)
Constant	0.954***
	(0.0748)
N	*32,746*

Notes: Linearized standard errors appear below the estimates. Model also includes dummy variables for survey year. Model is fit to data years 2006-2013 of the NHIS Sample Adult and Person File data on 55-64-year-olds. ***Statistically significant at the 1 percent level; **Statistically significant at the 5 percent level; *Statistically significant at the 10 percent level.

Table C.4: Age 64 Means and Estimated Mental Health Discontinuities by Predicted Insurance Tercile, NHIS 2006-2013

Outcome:	Did Not Get Mental Health Care Last Year (Costs)		Mental Health Visit Last Year		Kessler K6 [0-24]	
	Age 64 Mean (1)	RD Estimate (2)	Age 64 Mean (3)	RD Estimate (4)	Age 64 Mean (5)	RD Estimate (6)
Insurance Probability Tercile						
Tercile 1	3.08	-2.06**	4.96	0.07	3.04	0.02
(N = 18,550)		(0.79)		(1.13)		(0.26)
Tercile 2	1.88	-1.05*	6.80	0.54	1.99	0.19
(N = 18,988)		(0.61)		(1.32)		(0.18)
Tercile 3	0.69	-0.21	9.29	0.20	1.78	0.04
(N = 18,048)		(0.37)		(1.42)		(0.14)

Notes: Tercile assignment is based on predicted probabilities from the estimates in Table C.3. Odd-numbered columns contain the sample-weighted average among 64-year-olds. Even-numbered columns contain estimates of β_3 from Equation 3.1. Linearized standard errors appear in parentheses below the estimates. All models are fit to data years 2006-2013 of the NHIS Sample Adult and Person File data. ***Statistically significant at the 1 percent level; **Statistically significant at the 5 percent level; *Statistically significant at the 10 percent level.

C.2 Note on the Age-In-Quarters Field

The constructed age-in-quarters field may overstate respondent age in some cases. For example, a 64-year-old individual who is surveyed in January and who has a February birthdate will incorrectly appear as a 65-year-old in the derived age-in-quarters field. Methodology from Card et al. (2008) is used to correct for this; a uniform distribution of interview dates is assumed, and as a result, 50 percent of respondents are assumed to have been surveyed in the first six weeks of each quarter, and 50 percent of respondents are assumed to have been surveyed in the last six weeks of each quarter. This results in roughly one-half of individuals shifting down by one quarter in the derived age-in-quarters field.

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